

May 26, 2025

1 SML HW4 : Formula 1 World Championship Analysis Using Unsupervised Learning

1.0.1 Team Members: Alekhiya, Devi and Hrishabh

1.1 Question 1: Can we group F1 drivers by their race-day performance profiles across seasons using data from results, qualifying, lap times and pit stops?

```
[138]: %pip install yellowbrick
      %pip install plotly
      %pip install tabulate
```

Defaulting to user installation because normal site-packages is not writeable
Note: you may need to restart the kernel to use updated packages.

```
Requirement already satisfied: yellowbrick in
c:\users\hrishabh\appdata\roaming\python\python312\site-packages (1.5)
Requirement already satisfied: matplotlib!=3.0.0,>=2.0.2 in
c:\programdata\anaconda3\lib\site-packages (from yellowbrick) (3.8.4)
Requirement already satisfied: scipy>=1.0.0 in
c:\users\hrishabh\appdata\roaming\python\python312\site-packages (from
yellowbrick) (1.11.4)
Requirement already satisfied: scikit-learn>=1.0.0 in
c:\users\hrishabh\appdata\roaming\python\python312\site-packages (from
yellowbrick) (1.5.0)
Requirement already satisfied: numpy>=1.16.0 in
c:\programdata\anaconda3\lib\site-packages (from yellowbrick) (1.26.4)
Requirement already satisfied: cyclopy>=0.10.0 in
c:\programdata\anaconda3\lib\site-packages (from yellowbrick) (0.11.0)
Requirement already satisfied: contourpy>=1.0.1 in
c:\programdata\anaconda3\lib\site-packages (from
matplotlib!=3.0.0,>=2.0.2->yellowbrick) (1.2.0)
Requirement already satisfied: fonttools>=4.22.0 in
c:\programdata\anaconda3\lib\site-packages (from
matplotlib!=3.0.0,>=2.0.2->yellowbrick) (4.51.0)
Requirement already satisfied: kiwisolver>=1.3.1 in
c:\programdata\anaconda3\lib\site-packages (from
matplotlib!=3.0.0,>=2.0.2->yellowbrick) (1.4.4)
Requirement already satisfied: packaging>=20.0 in
```

```
c:\programdata\anaconda3\lib\site-packages (from
matplotlib!=3.0.0,>=2.0.2->yellowbrick) (23.2)
Requirement already satisfied: pillow>=8 in c:\programdata\anaconda3\lib\site-
packages (from matplotlib!=3.0.0,>=2.0.2->yellowbrick) (10.3.0)
Requirement already satisfied: pyparsing>=2.3.1 in
c:\programdata\anaconda3\lib\site-packages (from
matplotlib!=3.0.0,>=2.0.2->yellowbrick) (3.0.9)
Requirement already satisfied: python-dateutil>=2.7 in
c:\programdata\anaconda3\lib\site-packages (from
matplotlib!=3.0.0,>=2.0.2->yellowbrick) (2.9.0.post0)
Requirement already satisfied: joblib>=1.2.0 in
c:\programdata\anaconda3\lib\site-packages (from scikit-
learn>=1.0.0->yellowbrick) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
c:\users\hrishabh\appdata\roaming\python\python312\site-packages (from scikit-
learn>=1.0.0->yellowbrick) (3.6.0)
Requirement already satisfied: six>=1.5 in c:\programdata\anaconda3\lib\site-
packages (from python-dateutil>=2.7->matplotlib!=3.0.0,>=2.0.2->yellowbrick)
(1.16.0)
Defaulting to user installation because normal site-packages is not
writeableNote: you may need to restart the kernel to use updated packages.
```

```
Requirement already satisfied: plotly in c:\programdata\anaconda3\lib\site-
packages (5.22.0)
Requirement already satisfied: tenacity>=6.2.0 in
c:\programdata\anaconda3\lib\site-packages (from plotly) (8.2.2)
Requirement already satisfied: packaging in c:\programdata\anaconda3\lib\site-
packages (from plotly) (23.2)
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: tabulate in c:\programdata\anaconda3\lib\site-
packages (0.9.0)
Note: you may need to restart the kernel to use updated packages.
```

```
[139]: import re
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder, StandardScaler
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
from yellowbrick.cluster import KElbowVisualizer, SilhouetteVisualizer
from sklearn.metrics import silhouette_score
from collections import Counter
import plotly.graph_objects as go
from matplotlib.colors import LinearSegmentedColormap
```

```

from matplotlib import colors as mcolors
from tabulate import tabulate
from scipy.cluster.hierarchy import linkage, dendrogram, fcluster

```

1.1.1 Load Data

```

[140]: dataframes = {
        name: pd.read_csv(f"{name}.csv") for name in [
            "circuits", "constructor_results", "constructor_standings",
            ↪ "constructors",
            "driver_standings", "drivers", "lap_times", "pit_stops",
            "qualifying", "races", "results", "seasons",
            "sprint_results", "status"
        ]
    }

```

```

[141]: # Visualize shape and sample of each dataset
for name, df in dataframes.items():
    print(f"\n==== {name.upper()} ====")
    print(f"Shape: {df.shape}")
    print(df.head())

```

==== CIRCUITS ====

Shape: (77, 9)

	circuitId	circuitRef	name	location \
0	1	albert_park	Albert Park Grand Prix Circuit	Melbourne
1	2	sepang	Sepang International Circuit	Kuala Lumpur
2	3	bahrain	Bahrain International Circuit	Sakhir
3	4	catalunya	Circuit de Barcelona-Catalunya	Montmeló
4	5	istanbul	Istanbul Park	Istanbul

	country	lat	lng	alt \
0	Australia	-37.84970	144.96800	10
1	Malaysia	2.76083	101.73800	18
2	Bahrain	26.03250	50.51060	7
3	Spain	41.57000	2.26111	109
4	Turkey	40.95170	29.40500	130

	url
0	http://en.wikipedia.org/wiki/Melbourne_Grand_P...
1	http://en.wikipedia.org/wiki/Sepang_Internatio...
2	http://en.wikipedia.org/wiki/Bahrain_Internati...
3	http://en.wikipedia.org/wiki/Circuit_de_Barcel...
4	http://en.wikipedia.org/wiki/Istanbul_Park

==== CONSTRUCTOR_RESULTS ====

Shape: (12625, 5)

	constructorResultsId	raceId	constructorId	points	status
0	1	18	1	14.0	\N
1	2	18	2	8.0	\N
2	3	18	3	9.0	\N
3	4	18	4	5.0	\N
4	5	18	5	2.0	\N

==== CONSTRUCTOR_STANDINGS ====

Shape: (13391, 7)

	constructorStandingsId	raceId	constructorId	points	position	\
0	1	18	1	14.0	1	
1	2	18	2	8.0	3	
2	3	18	3	9.0	2	
3	4	18	4	5.0	4	
4	5	18	5	2.0	5	

	positionText	wins
0	1	1
1	3	0
2	2	0
3	4	0
4	5	0

==== CONSTRUCTORS ====

Shape: (212, 5)

	constructorId	constructorRef	name	nationality	\
0	1	mclaren	McLaren	British	
1	2	bmw_sauber	BMW Sauber	German	
2	3	williams	Williams	British	
3	4	renault	Renault	French	
4	5	toro_rosso	Toro Rosso	Italian	

	url
0	http://en.wikipedia.org/wiki/McLaren
1	http://en.wikipedia.org/wiki/BMW_Sauber
2	http://en.wikipedia.org/wiki/Williams_Grand_Pr...
3	http://en.wikipedia.org/wiki/Renault_in_Formul...
4	http://en.wikipedia.org/wiki/Scuderia_Toro_Rosso

==== DRIVER_STANDINGS ====

Shape: (34863, 7)

	driverStandingsId	raceId	driverId	points	position	positionText	wins
0	1	18	1	10.0	1	1	1
1	2	18	2	8.0	2	2	0
2	3	18	3	6.0	3	3	0
3	4	18	4	5.0	4	4	0
4	5	18	5	4.0	5	5	0

==== DRIVERS ====

Shape: (861, 9)

	driverId	driverRef	number	code	forename	surname	dob	\
0	1	hamilton	44	HAM	Lewis	Hamilton	1985-01-07	
1	2	heidfeld	\N	HEI	Nick	Heidfeld	1977-05-10	
2	3	rosberg	6	ROS	Nico	Rosberg	1985-06-27	
3	4	alonso	14	ALO	Fernando	Alonso	1981-07-29	
4	5	kovalainen	\N	KOV	Heikki	Kovalainen	1981-10-19	

	nationality	url
0	British	http://en.wikipedia.org/wiki/Lewis_Hamilton
1	German	http://en.wikipedia.org/wiki/Nick_Heidfeld
2	German	http://en.wikipedia.org/wiki/Nico_Rosberg
3	Spanish	http://en.wikipedia.org/wiki/Fernando_Alonso
4	Finnish	http://en.wikipedia.org/wiki/Heikki_Kovalainen

==== LAP_TIMES ====

Shape: (589081, 6)

	raceId	driverId	lap	position	time	milliseconds
0	841	20	1	1	1:38.109	98109
1	841	20	2	1	1:33.006	93006
2	841	20	3	1	1:32.713	92713
3	841	20	4	1	1:32.803	92803
4	841	20	5	1	1:32.342	92342

==== PIT_STOPS ====

Shape: (11371, 7)

	raceId	driverId	stop	lap	time	duration	milliseconds
0	841	153	1	1	17:05:23	26.898	26898
1	841	30	1	1	17:05:52	25.021	25021
2	841	17	1	11	17:20:48	23.426	23426
3	841	4	1	12	17:22:34	23.251	23251
4	841	13	1	13	17:24:10	23.842	23842

==== QUALIFYING ====

Shape: (10494, 9)

	qualifyId	raceId	driverId	constructorId	number	position	q1	\
0	1	18	1	1	22	1	1:26.572	
1	2	18	9	2	4	2	1:26.103	
2	3	18	5	1	23	3	1:25.664	
3	4	18	13	6	2	4	1:25.994	
4	5	18	2	2	3	5	1:25.960	

	q2	q3
0	1:25.187	1:26.714
1	1:25.315	1:26.869
2	1:25.452	1:27.079
3	1:25.691	1:27.178

4 1:25.518 1:27.236

==== RACES ====

Shape: (1125, 18)

	raceId	year	round	circuitId	name	date	\
0	1	2009	1	1	Australian Grand Prix	2009-03-29	
1	2	2009	2	2	Malaysian Grand Prix	2009-04-05	
2	3	2009	3	17	Chinese Grand Prix	2009-04-19	
3	4	2009	4	3	Bahrain Grand Prix	2009-04-26	
4	5	2009	5	4	Spanish Grand Prix	2009-05-10	

	time	url	fp1_date	\
0	06:00:00	http://en.wikipedia.org/wiki/2009_Australian_G...		\N
1	09:00:00	http://en.wikipedia.org/wiki/2009_Malaysian_Gr...		\N
2	07:00:00	http://en.wikipedia.org/wiki/2009_Chinese_Gran...		\N
3	12:00:00	http://en.wikipedia.org/wiki/2009_Bahrain_Gran...		\N
4	12:00:00	http://en.wikipedia.org/wiki/2009_Spanish_Gran...		\N

	fp1_time	fp2_date	fp2_time	fp3_date	fp3_time	quali_date	quali_time	\
0	\N	\N	\N	\N	\N	\N	\N	
1	\N	\N	\N	\N	\N	\N	\N	
2	\N	\N	\N	\N	\N	\N	\N	
3	\N	\N	\N	\N	\N	\N	\N	
4	\N	\N	\N	\N	\N	\N	\N	

	sprint_date	sprint_time
0	\N	\N
1	\N	\N
2	\N	\N
3	\N	\N
4	\N	\N

==== RESULTS ====

Shape: (26759, 18)

	resultId	raceId	driverId	constructorId	number	grid	position	\
0	1	18	1	1	22	1	1	
1	2	18	2	2	3	5	2	
2	3	18	3	3	7	7	3	
3	4	18	4	4	5	11	4	
4	5	18	5	1	23	3	5	

	positionText	positionOrder	points	laps	time	milliseconds	\
0	1	1	10.0	58	1:34:50.616	5690616	
1	2	2	8.0	58	+5.478	5696094	
2	3	3	6.0	58	+8.163	5698779	
3	4	4	5.0	58	+17.181	5707797	
4	5	5	4.0	58	+18.014	5708630	

	fastestLap	rank	fastestLapTime	fastestLapSpeed	statusId
0	39	2	1:27.452	218.300	1
1	41	3	1:27.739	217.586	1
2	41	5	1:28.090	216.719	1
3	58	7	1:28.603	215.464	1
4	43	1	1:27.418	218.385	1

==== SEASONS ====

Shape: (75, 2)

	year	url
0	2009	http://en.wikipedia.org/wiki/2009_Formula_One_...
1	2008	http://en.wikipedia.org/wiki/2008_Formula_One_...
2	2007	http://en.wikipedia.org/wiki/2007_Formula_One_...
3	2006	http://en.wikipedia.org/wiki/2006_Formula_One_...
4	2005	http://en.wikipedia.org/wiki/2005_Formula_One_...

==== SPRINT_RESULTS ====

Shape: (360, 16)

	resultId	raceId	driverId	constructorId	number	grid	position	\
0	1	1061	830	9	33	2	1	
1	2	1061	1	131	44	1	2	
2	3	1061	822	131	77	3	3	
3	4	1061	844	6	16	4	4	
4	5	1061	846	1	4	6	5	

	positionText	positionOrder	points	laps	time	milliseconds	\
0	1	1	3	17	25:38.426	1538426	
1	2	2	2	17	+1.430	1539856	
2	3	3	1	17	+7.502	1545928	
3	4	4	0	17	+11.278	1549704	
4	5	5	0	17	+24.111	1562537	

	fastestLap	fastestLapTime	statusId
0	14	1:30.013	1
1	17	1:29.937	1
2	17	1:29.958	1
3	16	1:30.163	1
4	16	1:30.566	1

==== STATUS ====

Shape: (139, 2)

	statusId	status
0	1	Finished
1	2	Disqualified
2	3	Accident
3	4	Collision
4	5	Engine

To characterize “race-day performance,” we are merging below tables:

results.csv

qualifying.csv

pit_stops.csv

lap_times.csv: average lap time per race

```
[142]: pd.set_option('display.max_columns', None)
results = dataframes["results"][["raceId", "driverId", "constructorId", "grid",
    ↪ "positionOrder", "points", "laps", "time", "milliseconds", "fastestLap",
    ↪ "rank", "fastestLapTime", "fastestLapSpeed", "statusId"]].
    ↪ rename(columns={"rank": "fastesLapRank", "milliseconds": "Total_time_ms",
    ↪ "positionOrder": "finalPosition"}).merge(dataframes["races"][["raceId",
    ↪ "year", "round", "circuitId", "name", "date"]], on="raceId", how="left")

#Merging with status table on statusId
results = results.merge(dataframes["status"], on="statusId", how="left")

# Merge with qualifying data
merged = results.merge(dataframes["qualifying"][["raceId", "driverId",
    ↪ "position", "q1", "q2", "q3"]].rename(columns={"position":
    ↪ "qualifyingPosition"}), on=["raceId", "driverId"], how="left")

merged = merged.merge(dataframes["drivers"][["driverId", "driverRef"]],
    ↪ on="driverId", how="left")

#Merge with pit_stops data
#df_pit = dataframes["pit_stops"].rename(columns={"stop": "pit_stop_number",
    ↪ "lap": "pit_stop_lap", "time": "pit_stop_time", "duration":
    ↪ "pit_stop_duration", "milliseconds": "pit_stop_duration_ms"})
#merged = merged.merge(df_pit, on=["raceId", "driverId"], how="left")

pit_summary = dataframes["pit_stops"].copy()
pit_summary["milliseconds"] = pd.to_numeric(pit_summary["milliseconds"],
    ↪ errors="coerce")
pit_summary = pit_summary.groupby(["raceId", "driverId"]).agg(
    total_pit_stops=('stop', 'count'),
    average_pit_duration_ms=('milliseconds', 'mean')
).reset_index()
merged = merged.merge(pit_summary, on=["raceId", "driverId"], how="left")

#Merge with lap_times data
avg_lap_time = dataframes["lap_times"].groupby(["raceId",
    ↪ "driverId"])[["milliseconds"].mean().reset_index(name="avg_lap_time")
avg_lap_time["avg_lap_time_str"] = avg_lap_time["avg_lap_time"].apply(
    lambda ms: f"{int(ms // 60000)}:{(ms % 60000) / 1000:.3f}" if pd.notna(ms)
    ↪ else None
)
```



```
merged = merged.merge(avg_lap_time.rename(columns = {"avg_lap_time":  
↳"avg_lap_time_ms"}), on=["raceId", "driverId"], how="left")
```

```
[143]: merged.info()
```

```
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 26759 entries, 0 to 26758  
Data columns (total 29 columns):  
#   Column                                Non-Null Count  Dtype  
---  -  
0   raceId                                26759 non-null  int64  
1   driverId                              26759 non-null  int64  
2   constructorId                         26759 non-null  int64  
3   grid                                  26759 non-null  int64  
4   finalPosition                         26759 non-null  int64  
5   points                                26759 non-null  float64  
6   laps                                  26759 non-null  int64  
7   time                                  26759 non-null  object  
8   Total_time_ms                         26759 non-null  object  
9   fastestLap                            26759 non-null  object  
10  fastestLapRank                        26759 non-null  object  
11  fastestLapTime                        26759 non-null  object  
12  fastestLapSpeed                       26759 non-null  object  
13  statusId                              26759 non-null  int64  
14  year                                  26759 non-null  int64  
15  round                                 26759 non-null  int64  
16  circuitId                             26759 non-null  int64  
17  name                                   26759 non-null  object  
18  date                                   26759 non-null  object  
19  status                                 26759 non-null  object  
20  qualifyingPosition                    10494 non-null  float64  
21  q1                                     10494 non-null  object  
22  q2                                     10472 non-null  object  
23  q3                                     10448 non-null  object  
24  driverRef                             26759 non-null  object  
25  total_pit_stops                       5575 non-null  float64  
26  average_pit_duration_ms               5575 non-null  float64  
27  avg_lap_time_ms                       11041 non-null  float64  
28  avg_lap_time_str                      11041 non-null  object  
dtypes: float64(5), int64(10), object(14)  
memory usage: 5.9+ MB
```

```
[144]: merged.isnull().sum()
```

```
[144]: raceId                                0  
       driverId                              0  
       constructorId                         0
```

```

grid                                0
finalPosition                      0
points                             0
laps                               0
time                               0
Total_time_ms                      0
fastestLap                         0
fastesLapRank                     0
fastestLapTime                     0
fastestLapSpeed                    0
statusId                           0
year                               0
round                              0
circuitId                         0
name                               0
date                               0
status                             0
qualifyingPosition                 16265
q1                                 16265
q2                                 16287
q3                                 16311
driverRef                          0
total_pit_stops                    21184
average_pit_duration_ms            21184
avg_lap_time_ms                    15718
avg_lap_time_str                   15718
dtype: int64

```

1.1.2 Data Cleaning and Transformation

The columns contains nearly a 50% of missing data. These columns is essential for clustering drivers based on performance. Imputing such a large percentage of missing values might introduce significant bias or noise into the analysis.

```

[145]: #dropping the NaN values
merged = merged.dropna(subset=['qualifyingPosition', 'q1', 'q2', 'q3',
↪ 'total_pit_stops', 'average_pit_duration_ms', 'avg_lap_time_ms',
↪ 'avg_lap_time_str']).reset_index(drop=True)

```

```

[146]: merged.isnull().sum().sum()

```

```

[146]: 0

```

```

[147]: #Removing the values with \N in the data.
merged.replace(to_replace='\\N', value=np.nan, inplace=True)
merged.dropna(inplace=True)

```

```

[148]: merged.shape

```

[148]: (2020, 29)

```
[149]: #Checking duplicates
merged[merged.duplicated()]
```

[149]: Empty DataFrame
Columns: [raceId, driverId, constructorId, grid, finalPosition, points, laps, time, Total_time_ms, fastestLap, fastestLapRank, fastestLapTime, fastestLapSpeed, statusId, year, round, circuitId, name, date, status, qualifyingPosition, q1, q2, q3, driverRef, total_pit_stops, average_pit_duration_ms, avg_lap_time_ms, avg_lap_time_str]
Index: []

```
[150]: merged['year'].unique()
```

[150]: array([2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023, 2024], dtype=int64)

```
[151]: # position change between starting grid position and the final position
merged["position_change"] = merged["grid"] - merged["finalPosition"].astype(int)
```

```
[152]: merged.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 2020 entries, 0 to 5500
Data columns (total 30 columns):
#   Column                Non-Null Count  Dtype
---  -
0   raceId                2020 non-null  int64
1   driverId              2020 non-null  int64
2   constructorId         2020 non-null  int64
3   grid                  2020 non-null  int64
4   finalPosition         2020 non-null  int64
5   points                2020 non-null  float64
6   laps                  2020 non-null  int64
7   time                  2020 non-null  object
8   Total_time_ms         2020 non-null  object
9   fastestLap            2020 non-null  object
10  fastestLapRank        2020 non-null  object
11  fastestLapTime        2020 non-null  object
12  fastestLapSpeed       2020 non-null  object
13  statusId              2020 non-null  int64
14  year                  2020 non-null  int64
15  round                  2020 non-null  int64
16  circuitId             2020 non-null  int64
17  name                   2020 non-null  object
18  date                   2020 non-null  object
19  status                 2020 non-null  object
```

```

20 qualifyingPosition      2020 non-null   float64
21 q1                      2020 non-null   object
22 q2                      2020 non-null   object
23 q3                      2020 non-null   object
24 driverRef               2020 non-null   object
25 total_pit_stops         2020 non-null   float64
26 average_pit_duration_ms 2020 non-null   float64
27 avg_lap_time_ms         2020 non-null   float64
28 avg_lap_time_str        2020 non-null   object
29 position_change         2020 non-null   int64
dtypes: float64(5), int64(11), object(14)
memory usage: 489.2+ KB

```

```
[153]: #merged["pit_stop_time"] = pd.to_datetime(merged["pit_stop_time"],
        ↪errors="coerce", format="%H:%M:%S").dt.time
```

```
[154]: merged.select_dtypes(include="object").columns
```

```
[154]: Index(['time', 'Total_time_ms', 'fastestLap', 'fastesLapRank',
        'fastestLapTime', 'fastestLapSpeed', 'name', 'date', 'status', 'q1',
        'q2', 'q3', 'driverRef', 'avg_lap_time_str'],
        dtype='object')
```

```
[155]: def time_str_to_ms(t):
        if pd.isna(t): return np.nan
        t = str(t).strip()
        if re.match(r"^\d+:\d+\.\d+$", t): # Matches '1:29.844' style
            minutes, rest = t.split(":")
            seconds = float(rest)
            return int(minutes) * 60000 + seconds * 1000

        # Apply to time columns of type object to convert into milliseconds of type
        ↪float.
merged["fastestLapTime_ms"] = merged["fastestLapTime"].apply(time_str_to_ms).
        ↪astype("Int64")
merged["q1_ms"] = merged["q1"].apply(time_str_to_ms).astype("Int64")
merged["q2_ms"] = merged["q2"].apply(time_str_to_ms).astype("Int64")
merged["q3_ms"] = merged["q3"].apply(time_str_to_ms).astype("Int64")
merged["Total_time_ms"] = pd.to_numeric(merged["Total_time_ms"],
        ↪errors="coerce").astype("Int64")
```

```
[156]: merged["fastestLap"] = pd.to_numeric(merged["fastestLap"], errors="coerce").
        ↪astype("Int64")
merged["fastesLapRank"] = pd.to_numeric(merged["fastesLapRank"],
        ↪errors="coerce").astype("Int64")
merged["fastestLapSpeed"] = pd.to_numeric(merged["fastestLapSpeed"],
        ↪errors="coerce").astype("float64")
```

```
[157]: #Encoding the qualitative variable status
le = LabelEncoder()
merged["status_encoded"] = le.fit_transform(merged["status"])
print(dict(zip(le.classes_, le.transform(le.classes_))))
```

```
{'Disqualified': 0, 'Finished': 1, 'Power Unit': 2}
```

```
[158]: final_data = merged.drop(columns = ['time', 'fastestLapTime', 'q1', 'q2', 'q3',
↳ 'driverRef', 'avg_lap_time_str', 'name', 'status', 'date'])
```

Columns like raceId, driverId, and constructorId are numerically stored, but: They are still categorical identifiers — just with numeric format. Their values do not carry mathematical meaning (e.g., driverId = 10 isn't "twice" driverId = 5). So removing those columns and performing SVD on the remaining features.

```
[159]: scaler = StandardScaler()
X_features = final_data.drop(columns=["raceId", "driverId", "constructorId",
↳ "circuitId", "statusId", "round", "status_encoded", "year", "laps"])
X_scaled = StandardScaler().fit_transform(X_features)
data_scaled_df = pd.DataFrame(X_scaled, columns=X_features.columns)
```

```
[160]: final_data.head()
```

```
[160]:
```

	raceId	driverId	constructorId	grid	finalPosition	points	laps	\
0	841	20	9	1	1	25.0	58	
1	841	1	1	2	2	18.0	58	
2	841	808	4	6	3	15.0	58	
3	841	4	6	5	4	12.0	58	
4	841	17	9	3	5	10.0	58	

	Total_time_ms	fastestLap	fastesLapRank	fastestLapSpeed	statusId	year	\
0	5370259	44	4	212.488	1	2011	
1	5392556	41	8	211.382	1	2011	
2	5400819	55	7	211.969	1	2011	
3	5402031	49	2	213.336	1	2011	
4	5408430	50	3	213.066	1	2011	

	round	circuitId	qualifyingPosition	total_pit_stops	\
0	1	1	1.0	2.0	
1	1	1	2.0	2.0	
2	1	1	6.0	2.0	
3	1	1	5.0	3.0	
4	1	1	3.0	3.0	

	average_pit_duration_ms	avg_lap_time_ms	position_change	\
0	23319.500000	92590.672414	0	
1	23213.000000	92975.103448	0	
2	25109.000000	93117.568966	3	

3	24055.000000	93138.465517	1
4	24058.666667	93248.793103	-2

	fastestLapTime_ms	q1_ms	q2_ms	q3_ms	status_encoded
0	89844	85296	84090	83529	1
1	90314	85384	84595	84307	1
2	90064	85543	85582	85247	1
3	89487	85707	85242	84974	1
4	89600	85900	84658	84395	1

```
[161]: data_scaled_df.head()
```

```
[161]:
```

	grid	finalPosition	points	Total_time_ms	fastestLap	\
0	-1.290033	-1.235402	1.737068	-0.439229	-0.391093	
1	-0.964747	-0.912358	0.794654	-0.420336	-0.635854	
2	0.336397	-0.589315	0.390762	-0.413335	0.506365	
3	0.011111	-0.266271	-0.013130	-0.412308	0.016842	
4	-0.639461	0.056772	-0.282391	-0.406886	0.098430	

	fastesLapRank	fastestLapSpeed	qualifyingPosition	total_pit_stops	\
0	-0.513603	0.236956	-1.414751	-0.027390	
1	0.465612	0.184532	-1.046952	-0.027390	
2	0.220808	0.212356	0.424243	-0.027390	
3	-1.003211	0.277152	0.056444	1.016529	
4	-0.758407	0.264354	-0.679154	1.016529	

	average_pit_duration_ms	avg_lap_time_ms	position_change	\
0	-0.269378	-0.389816	-0.048314	
1	-0.269930	-0.369424	-0.048314	
2	-0.260102	-0.361867	0.975400	
3	-0.265566	-0.360759	0.292924	
4	-0.265547	-0.354907	-0.730789	

	fastestLapTime_ms	q1_ms	q2_ms	q3_ms
0	-0.065757	-0.250179	-0.293561	-0.325067
1	-0.025557	-0.243077	-0.252019	-0.262457
2	-0.046940	-0.230246	-0.170826	-0.186809
3	-0.096292	-0.217011	-0.198795	-0.208779
4	-0.086627	-0.201436	-0.246836	-0.255375

2 MATRIX COMPLETION

```
[162]: # Created a boolean mask 'non_nan' that is True for each entry in X that isn't
        ↪ NaN (i.e., observed data) and False for missing values

def matrix_completion_svd(
    X: np.ndarray,
```

```

    rank: int = 5,
    max_iters: int = 100,
    tol: float = 1e-6,
    verbose: bool = False
) -> np.ndarray:
    non_nan = ~np.isnan(X)
    X_filled = X.copy()

    # Finding all missing entries in X_filled and replaces each with the mean
    # of its respective column.
    col_means = np.nanmean(X, axis=0)
    missing_idx = np.where(~non_nan)
    X_filled[missing_idx] = np.take(col_means, missing_idx[1])

    for it in range(1, max_iters + 1):
        # Constructing low-rank matrix again
        U, s, Vt = np.linalg.svd(X_filled, full_matrices=False)
        S = np.diag(s[:rank])
        X_lowrank = U[:, :rank] @ S @ Vt[:rank, :]
        X_new = X_lowrank.copy()
        X_new[non_nan] = X[non_nan]

        # Checking convergence
        rel_change = np.linalg.norm(X_new - X_filled) / np.linalg.norm(X_filled)
        if verbose:
            print(f"[Iter {it:3d}/{max_iters}] rel-change = {rel_change:.2e}")

        X_filled = X_new
        if rel_change < tol:
            if verbose:
                print("Converged.")
            break

    return X_filled

# Pivot the results DataFrame into a driver-by-race points matrix and then
# converting it to a NumPy array with NaNs for missing scores
results_df = dataframes['results']
matrix_df = (
    results_df
    .pivot_table(
        index='driverId',
        columns='raceId',
        values='points'
    )
)

```

```

X = matrix_df.values

X_completed = matrix_completion_svd(X, rank=5, max_iters=100, tol=1e-6,
↳ verbose=True)

completed_df = pd.DataFrame(
    X_completed,
    index=matrix_df.index,
    columns=matrix_df.columns
)

print("Missing before:", np.isnan(X).sum())
print("Missing after: ", np.isnan(X_completed).sum())

```

```

[Iter  1/100] rel-change = 5.06e-02
[Iter  2/100] rel-change = 3.07e-02
[Iter  3/100] rel-change = 2.32e-02
[Iter  4/100] rel-change = 1.92e-02
[Iter  5/100] rel-change = 1.66e-02
[Iter  6/100] rel-change = 1.45e-02
[Iter  7/100] rel-change = 1.28e-02
[Iter  8/100] rel-change = 1.15e-02
[Iter  9/100] rel-change = 1.05e-02
[Iter 10/100] rel-change = 9.84e-03
[Iter 11/100] rel-change = 9.39e-03
[Iter 12/100] rel-change = 9.08e-03
[Iter 13/100] rel-change = 8.89e-03
[Iter 14/100] rel-change = 8.78e-03
[Iter 15/100] rel-change = 8.74e-03
[Iter 16/100] rel-change = 8.74e-03
[Iter 17/100] rel-change = 8.76e-03
[Iter 18/100] rel-change = 8.75e-03
[Iter 19/100] rel-change = 8.68e-03
[Iter 20/100] rel-change = 8.54e-03
[Iter 21/100] rel-change = 8.32e-03
[Iter 22/100] rel-change = 8.07e-03
[Iter 23/100] rel-change = 7.81e-03
[Iter 24/100] rel-change = 7.60e-03
[Iter 25/100] rel-change = 7.43e-03
[Iter 26/100] rel-change = 7.33e-03
[Iter 27/100] rel-change = 7.26e-03
[Iter 28/100] rel-change = 7.23e-03
[Iter 29/100] rel-change = 7.21e-03
[Iter 30/100] rel-change = 7.18e-03
[Iter 31/100] rel-change = 7.12e-03
[Iter 32/100] rel-change = 7.04e-03
[Iter 33/100] rel-change = 6.92e-03
[Iter 34/100] rel-change = 6.77e-03

```


[Iter 35/100] rel-change = 6.61e-03
[Iter 36/100] rel-change = 6.44e-03
[Iter 37/100] rel-change = 6.27e-03
[Iter 38/100] rel-change = 6.11e-03
[Iter 39/100] rel-change = 5.96e-03
[Iter 40/100] rel-change = 5.83e-03
[Iter 41/100] rel-change = 5.70e-03
[Iter 42/100] rel-change = 5.58e-03
[Iter 43/100] rel-change = 5.46e-03
[Iter 44/100] rel-change = 5.35e-03
[Iter 45/100] rel-change = 5.24e-03
[Iter 46/100] rel-change = 5.14e-03
[Iter 47/100] rel-change = 5.05e-03
[Iter 48/100] rel-change = 4.95e-03
[Iter 49/100] rel-change = 4.87e-03
[Iter 50/100] rel-change = 4.79e-03
[Iter 51/100] rel-change = 4.72e-03
[Iter 52/100] rel-change = 4.65e-03
[Iter 53/100] rel-change = 4.58e-03
[Iter 54/100] rel-change = 4.52e-03
[Iter 55/100] rel-change = 4.47e-03
[Iter 56/100] rel-change = 4.41e-03
[Iter 57/100] rel-change = 4.35e-03
[Iter 58/100] rel-change = 4.29e-03
[Iter 59/100] rel-change = 4.23e-03
[Iter 60/100] rel-change = 4.17e-03
[Iter 61/100] rel-change = 4.11e-03
[Iter 62/100] rel-change = 4.05e-03
[Iter 63/100] rel-change = 3.99e-03
[Iter 64/100] rel-change = 3.93e-03
[Iter 65/100] rel-change = 3.88e-03
[Iter 66/100] rel-change = 3.83e-03
[Iter 67/100] rel-change = 3.78e-03
[Iter 68/100] rel-change = 3.74e-03
[Iter 69/100] rel-change = 3.70e-03
[Iter 70/100] rel-change = 3.67e-03
[Iter 71/100] rel-change = 3.64e-03
[Iter 72/100] rel-change = 3.61e-03
[Iter 73/100] rel-change = 3.58e-03
[Iter 74/100] rel-change = 3.56e-03
[Iter 75/100] rel-change = 3.54e-03
[Iter 76/100] rel-change = 3.51e-03
[Iter 77/100] rel-change = 3.49e-03
[Iter 78/100] rel-change = 3.47e-03
[Iter 79/100] rel-change = 3.45e-03
[Iter 80/100] rel-change = 3.43e-03
[Iter 81/100] rel-change = 3.41e-03
[Iter 82/100] rel-change = 3.39e-03

```

[Iter 83/100] rel-change = 3.37e-03
[Iter 84/100] rel-change = 3.35e-03
[Iter 85/100] rel-change = 3.33e-03
[Iter 86/100] rel-change = 3.31e-03
[Iter 87/100] rel-change = 3.29e-03
[Iter 88/100] rel-change = 3.28e-03
[Iter 89/100] rel-change = 3.26e-03
[Iter 90/100] rel-change = 3.25e-03
[Iter 91/100] rel-change = 3.23e-03
[Iter 92/100] rel-change = 3.21e-03
[Iter 93/100] rel-change = 3.20e-03
[Iter 94/100] rel-change = 3.18e-03
[Iter 95/100] rel-change = 3.17e-03
[Iter 96/100] rel-change = 3.15e-03
[Iter 97/100] rel-change = 3.13e-03
[Iter 98/100] rel-change = 3.12e-03
[Iter 99/100] rel-change = 3.10e-03
[Iter 100/100] rel-change = 3.08e-03
Missing before: 941957
Missing after: 0

```

```
[163]: completed_df.sample(5)
```

```

[163]: raceId      1          2          3          4          5          6      \
driverId
292      1.814739  0.786134  1.048315  1.775408  1.526402  1.981822
475      4.575409  1.586142  0.366874  2.478301  3.401873  5.159508
592      1.853458  0.791756  1.018651  1.763092  1.563269  2.036441
94       1.070475  0.543267  1.059953  1.560002  1.104981  1.166037
771      1.936208  0.819481  1.010812  1.792873  1.613124  2.125509

raceId      7          8          9          10          11          12      \
driverId
292      0.972037  1.129973  1.026457  1.924568  2.648174  1.659775
475      1.743818  0.839924  1.220544  2.336195  4.303195  3.499378
592      0.992878  1.108163  1.028112  1.888506  2.622518  1.680069
94       0.754489  0.974267  0.833684  1.415934  1.856763  1.192180
771      1.013251  1.111511  1.039051  1.932180  2.703608  1.730684

raceId      13          14          15          16          17          18      \
driverId
292      2.121762  2.175089  1.824604  1.260683  1.007089  2.020801
475      5.427427  2.719848  1.192185  1.260261  0.848841  2.333121
592      2.172447  2.147189  1.761493  1.251446  0.995033  1.974924
94       1.335904  1.957102  1.651306  1.183665  0.959248  1.613380
771      2.264141  2.186021  1.772075  1.261654  0.994754  2.019753

```

raceId	19	20	21	22	23	24	\
driverId							
292	1.745402	1.687956	1.871888	2.131866	1.538772	1.355564	
475	3.747766	4.047992	3.725576	3.595823	0.618983	2.350418	
592	1.765451	1.722964	1.892485	2.131649	1.482830	1.352668	
94	1.215117	1.144969	1.427547	1.738480	1.563324	1.024512	
771	1.827312	1.789696	1.950947	2.189384	1.486792	1.392419	

raceId	25	26	27	28	29	30	\
driverId							
292	1.639756	2.394658	2.020288	1.775563	1.737482	1.829892	
475	4.168735	3.253206	2.003001	3.872328	1.568523	2.495527	
592	1.682554	2.351833	1.966459	1.793981	1.692671	1.817212	
94	1.077378	1.900501	1.804426	1.209195	1.625872	1.696334	
771	1.751278	2.409891	1.999344	1.861157	1.715941	1.850262	

raceId	31	32	33	34	35	36	\
driverId							
292	1.283276	1.838163	1.658804	2.344105	2.017779	2.309052	
475	1.481532	2.848424	4.924094	3.870784	4.182831	3.530001	
592	1.275173	1.829827	1.736429	2.338178	2.049397	2.310880	
94	1.299202	1.397540	1.136393	1.942663	1.639933	2.083917	
771	1.283696	1.877542	1.810315	2.400432	2.108911	2.346703	

raceId	37	38	39	40	41	42	\
driverId							
292	2.284687	2.203220	1.894653	2.012765	1.975772	2.144922	
475	3.673447	2.481790	3.486211	4.213475	0.357582	3.780114	
592	2.289686	2.175099	1.899214	2.043158	1.887827	2.153528	
94	2.057723	2.161225	1.421705	1.625677	2.163500	1.770570	
771	2.333764	2.196838	1.964996	2.111087	1.872602	2.212401	

raceId	43	44	45	46	47	48	\
driverId							
292	2.170760	2.245304	1.304335	2.228423	2.141819	2.190798	
475	2.332903	3.547132	3.739811	3.715617	4.831649	4.590076	
592	2.146490	2.254451	1.367500	2.220172	2.177575	2.218464	
94	2.203145	2.078422	0.902177	1.746572	1.546514	1.625557	
771	2.156390	2.289153	1.425912	2.281846	2.256904	2.294185	

raceId	49	50	51	52	53	54	\
driverId							
292	2.135568	1.897079	1.876986	2.079719	1.054363	1.408579	
475	4.756592	2.301497	5.238711	5.261249	5.787261	4.742641	
592	2.170576	1.858787	1.952534	2.132927	1.188259	1.489427	
94	1.505365	1.561873	1.344539	1.350282	0.236170	0.901413	
771	2.248735	1.898771	2.027515	2.221007	1.287918	1.569188	

raceId	55	56	57	58	59	60	\
driverId							
292	1.790871	1.118357	1.348269	1.255670	1.457083	1.323940	
475	4.215889	5.776382	5.620638	5.834662	4.756677	5.950021	
592	1.838696	1.241578	1.441718	1.371292	1.524051	1.440766	
94	1.393165	0.277134	0.417902	0.447581	0.759200	0.518936	
771	1.892067	1.348563	1.551231	1.476195	1.611522	1.545309	

raceId	61	62	63	64	65	66	\
driverId							
292	1.224862	1.210725	1.417270	1.499524	2.117559	2.077444	
475	5.673236	4.496808	6.388352	6.266826	2.462214	5.221316	
592	1.337375	1.269433	1.534229	1.611113	2.079274	2.128691	
94	0.431317	0.404524	0.459287	0.593876	1.866757	1.460698	
771	1.436953	1.366188	1.655697	1.726719	2.115925	2.223445	

raceId	67	68	69	70	71	72	\
driverId							
292	1.019059	1.183322	2.203045	2.081111	1.579986	1.541099	
475	5.638693	5.998535	4.934609	5.670763	2.747357	3.998041	
592	1.132426	1.299847	2.254062	2.151857	1.582825	1.582984	
94	0.085020	0.243539	1.815423	1.444826	1.098404	1.024403	
771	1.238160	1.418327	2.323771	2.246828	1.627646	1.650847	

raceId	73	74	75	76	77	78	\
driverId							
292	1.504336	1.608580	1.615538	1.824155	1.696132	1.735895	
475	4.114039	4.604705	4.777802	4.107357	4.097749	4.032415	
592	1.567572	1.662054	1.700495	1.874038	1.725029	1.757513	
94	1.084477	0.893961	1.167629	1.372901	1.013830	0.833424	
771	1.622557	1.752381	1.757821	1.922854	1.801523	1.834015	

raceId	79	80	81	82	83	84	\
driverId							
292	1.507336	1.277060	1.414468	1.298959	1.431448	1.458562	
475	3.250402	5.897297	5.877035	5.481992	4.543640	5.124866	
592	1.485234	1.401372	1.530609	1.407540	1.490263	1.560191	
94	0.403275	0.530472	0.718737	0.638015	0.594348	1.008485	
771	1.580102	1.496286	1.625487	1.502758	1.570281	1.625806	

raceId	85	86	87	88	89	90	\
driverId							
292	1.507233	1.778627	1.537127	1.353656	1.548848	1.759097	
475	4.945777	3.873833	6.058150	3.993115	4.304342	5.531743	
592	1.591803	1.828861	1.644067	1.428894	1.620768	1.808390	
94	1.028594	1.447023	0.683829	0.919151	1.208958	0.542103	

771	1.664533	1.869013	1.747515	1.475727	1.671429	1.934025
-----	----------	----------	----------	----------	----------	----------

raceId	91	92	93	94	95	96	\
driverId							
292	1.760500	1.677404	1.473241	1.675189	2.036818	1.552739	
475	5.158302	4.555866	5.881545	4.756939	2.724474	4.898006	
592	1.801209	1.699954	1.562439	1.699538	2.003364	1.598728	
94	0.644021	0.557573	0.408992	0.495497	1.655896	0.444677	
771	1.918831	1.808300	1.684712	1.814115	2.052894	1.710120	

raceId	97	98	99	100	101	102	\
driverId							
292	1.588257	1.903862	1.611202	1.621167	1.464254	1.764394	
475	4.759436	3.645349	5.746352	5.696552	4.795812	5.597675	
592	1.624646	1.875725	1.683090	1.691665	1.529814	1.817672	
94	0.451985	0.775986	0.432901	0.405439	0.550192	0.582197	
771	1.730859	1.970734	1.805311	1.807713	1.628803	1.943310	

raceId	103	104	105	106	107	108	\
driverId							
292	1.849027	2.028106	1.726826	1.339712	1.786590	1.738333	
475	4.829055	4.121853	4.595631	5.285462	5.064830	3.883732	
592	1.879734	2.014044	1.778411	1.419065	1.844120	1.755725	
94	0.819501	0.937886	1.108356	0.347903	1.020873	0.938819	
771	1.974775	2.115153	1.850941	1.526894	1.929982	1.829502	

raceId	109	110	111	112	113	114	\
driverId							
292	1.742340	1.535890	1.787728	1.583109	1.705041	1.604964	
475	4.973109	3.419152	5.410716	5.375434	4.669059	5.592135	
592	1.797622	1.573280	1.836078	1.644935	1.738467	1.685335	
94	0.924747	1.210718	0.568291	0.460856	0.574929	0.672475	
771	1.879952	1.613659	1.949044	1.764275	1.836233	1.787503	

raceId	115	116	117	118	119	120	\
driverId							
292	1.597465	1.666409	1.728971	2.006835	1.655764	1.387862	
475	5.487445	4.387690	3.916519	4.297774	3.310377	4.604792	
592	1.662047	1.702344	1.743490	2.007245	1.664827	1.474479	
94	0.439447	0.829746	0.827518	0.994189	1.109441	0.861050	
771	1.780414	1.791264	1.823605	2.098224	1.727175	1.538180	

raceId	121	122	123	124	125	126	\
driverId							
292	1.947215	1.567737	1.879325	0.920871	1.024913	1.005883	
475	5.048877	4.655456	2.942430	4.861007	3.895399	4.001204	
592	1.974334	1.610563	1.857193	1.016209	1.085552	1.057306	

94	0.805674	0.617683	1.207743	0.017389	0.416516	0.082919
771	2.086038	1.704222	1.907545	1.115194	1.161088	1.150557

raceId	127	128	129	130	131	132	\
driverId							
292	1.182130	1.109700	1.173980	1.102971	1.156578	1.322503	
475	4.178480	4.064586	4.126174	1.575744	3.327526	3.424443	
592	1.219393	1.157045	1.208487	1.070783	1.170516	1.333256	
94	0.122950	0.209697	0.105230	0.454005	0.174418	0.450806	
771	1.322867	1.252198	1.312319	1.117763	1.254664	1.411519	

raceId	133	134	135	136	137	138	\
driverId							
292	1.347712	1.035294	1.154978	1.391428	1.248493	1.323971	
475	3.622418	4.788336	4.296822	2.770121	3.737777	2.458248	
592	1.357412	1.116484	1.200345	1.372129	1.265778	1.300487	
94	0.392328	0.070167	0.125351	0.513984	0.197441	0.543998	
771	1.451293	1.214530	1.304304	1.443168	1.363490	1.367405	

raceId	139	140	141	142	143	144	\
driverId							
292	1.455007	1.180425	1.222635	1.237423	1.174982	1.224906	
475	2.284014	4.562204	2.270398	2.336120	0.780751	0.326275	
592	1.412867	1.234553	1.201899	1.216229	1.122020	1.161667	
94	0.595581	0.124365	0.317082	0.282917	0.619415	0.866912	
771	1.481678	1.338325	1.269166	1.287547	1.151664	1.172242	

raceId	145	146	147	148	149	150	\
driverId							
292	1.164070	1.247734	1.352853	0.935545	1.074264	1.151623	
475	3.039502	1.218994	2.376155	2.345832	3.044731	2.858275	
592	1.173776	1.203034	1.326566	0.950192	1.089183	1.147879	
94	0.362030	0.548170	0.487615	0.326218	0.129581	0.177071	
771	1.253249	1.240640	1.397558	1.000128	1.170815	1.228764	

raceId	151	152	153	154	155	156	\
driverId							
292	0.929992	1.379421	1.207656	0.977106	1.207948	0.836882	
475	1.477221	1.695603	2.381840	1.931516	3.069720	0.065141	
592	0.929710	1.341315	1.190315	0.969939	1.216456	0.804449	
94	0.377787	1.030781	0.242629	0.137878	0.566716	0.432926	
771	0.961921	1.377534	1.261865	1.027868	1.287356	0.810484	

raceId	157	158	159	160	161	162	\
driverId							
292	1.007845	1.255208	0.909277	1.167452	1.186840	1.361356	
475	2.665569	3.615890	4.937428	2.097802	1.100154	1.171932	

592	1.020357	1.269387	1.000513	1.161899	1.169287	1.341826
94	0.113484	0.282944	-0.019801	0.354078	0.688675	0.915294
771	1.092878	1.365405	1.107534	1.220073	1.184402	1.348603

raceId	163	164	165	166	167	168	\
driverId							
292	1.036916	1.344248	1.133992	1.424277	1.440429	1.511374	
475	2.883215	0.071020	4.519799	-0.939647	0.346128	2.314209	
592	1.065949	1.269448	1.195760	1.324450	1.399403	1.507680	
94	0.134859	0.981636	0.092111	1.198255	1.249678	0.998434	
771	1.134760	1.268131	1.296789	1.301513	1.386623	1.534865	

raceId	169	170	171	172	173	174	\
driverId							
292	1.242041	1.145961	0.972103	1.240184	1.156654	1.201539	
475	2.171409	3.173715	3.569710	1.969822	3.071392	1.548409	
592	1.255025	1.204894	1.028647	1.203073	1.187037	1.166691	
94	0.590599	0.521659	0.146505	0.396330	0.275710	0.362900	
771	1.290889	1.251950	1.106248	1.274626	1.257909	1.222738	

raceId	175	176	177	178	179	180	\
driverId							
292	1.086817	1.032262	1.084488	0.878494	1.168188	1.055548	
475	1.240195	2.559974	3.391107	2.997276	1.945728	2.092807	
592	1.074501	1.082346	1.108678	0.929374	1.195035	1.104674	
94	0.940884	0.555062	0.074156	0.184971	0.718439	0.928817	
771	1.088513	1.120420	1.195898	0.999245	1.215116	1.111856	

raceId	181	182	183	184	185	186	\
driverId							
292	1.249149	1.298957	1.263163	1.073636	1.442610	1.437195	
475	1.552464	1.126167	1.735440	0.614914	2.782076	2.370119	
592	1.240136	1.271173	1.265310	1.045968	1.476243	1.447283	
94	0.909301	1.004333	0.822108	1.043932	0.782912	0.745767	
771	1.259962	1.279978	1.294475	1.044784	1.518217	1.488458	

raceId	187	188	189	190	191	192	\
driverId							
292	1.242285	1.134707	1.045277	1.067389	1.290083	1.095184	
475	1.050172	0.887934	2.154175	2.690081	1.008380	1.800508	
592	1.198776	1.088955	1.065004	1.121730	1.290609	1.120517	
94	0.898125	0.840717	0.570830	0.591792	1.181332	0.673797	
771	1.219077	1.104759	1.108337	1.161406	1.282550	1.140106	

raceId	193	194	195	196	197	198	\
driverId							
292	0.959020	1.219168	1.197913	1.055069	0.802695	1.033351	

475	2.988024	1.190919	1.652581	1.844945	2.974822	2.655373
592	1.006251	1.184223	1.207093	1.098024	0.837067	1.062458
94	0.229138	0.680603	0.736375	1.010877	0.021156	0.379215
771	1.074469	1.220397	1.227423	1.101954	0.917339	1.129490

raceId	199	200	201	202	203	204	\
driverId							
292	0.882300	1.183309	1.344005	1.152409	1.159580	0.968459	
475	3.129318	1.884175	2.400630	3.130955	4.721447	3.434340	
592	0.939993	1.208309	1.380355	1.177503	1.251326	1.021144	
94	0.160195	0.760453	1.031637	0.348025	0.756858	0.187384	
771	1.009583	1.227861	1.401487	1.256770	1.317246	1.100114	

raceId	205	206	207	208	209	210	\
driverId							
292	1.075307	1.252338	0.970665	1.481977	1.478365	0.951173	
475	2.389183	2.326615	1.295312	0.968890	0.615107	2.113111	
592	1.120282	1.302435	0.961346	1.435211	1.426429	0.965550	
94	0.559807	1.089941	0.378981	1.402724	1.566728	0.530815	
771	1.154341	1.311570	0.991323	1.457239	1.434850	1.014056	

raceId	211	212	213	214	215	216	\
driverId							
292	0.967617	1.511487	0.925028	1.118164	1.603626	0.938703	
475	2.230745	0.636868	3.121843	2.551293	0.681647	2.508323	
592	0.956071	1.436684	0.954112	1.123373	1.531748	0.966441	
94	0.145721	1.430366	0.159022	0.462418	1.602117	0.317551	
771	1.029273	1.464122	1.037464	1.197131	1.549121	1.019484	

raceId	217	218	219	220	221	222	\
driverId							
292	1.466541	0.892157	1.253048	1.521731	1.546595	0.920986	
475	2.856121	2.791597	0.564978	0.252682	0.577693	2.703226	
592	1.472753	0.916758	1.198899	1.443970	1.475274	0.952836	
94	1.240208	0.211104	0.996501	1.471794	1.599444	0.257564	
771	1.529564	0.993937	1.210597	1.454660	1.491959	1.021453	

raceId	223	224	225	226	227	228	\
driverId							
292	1.204131	1.376979	1.160250	1.472343	1.390828	1.152555	
475	0.826259	4.393384	5.736286	4.503194	2.110194	5.646053	
592	1.201779	1.461102	1.287727	1.536569	1.367939	1.263703	
94	1.125402	1.162282	0.550279	1.152751	0.943104	0.349686	
771	1.193740	1.518912	1.377774	1.605453	1.425968	1.365972	

raceId	229	230	231	232	233	234	\
driverId							

292	1.133395	1.077866	1.426837	1.444041	1.508792	1.415947
475	-0.034907	2.627633	4.268817	4.536374	0.690229	5.140018
592	1.069188	1.087810	1.497304	1.522396	1.454622	1.499804
94	1.043404	0.434417	1.155706	1.162773	1.427348	0.875780
771	1.064526	1.162828	1.555471	1.585323	1.465353	1.586225

raceId	235	236	237	238	239	240	\
driverId							
292	1.595696	1.153719	0.973112	1.489577	1.089165	0.957986	
475	2.940144	3.423239	3.041379	3.519871	6.044559	2.560910	
592	1.612622	1.195529	1.002527	1.518823	1.234150	0.977929	
94	1.522258	0.491550	0.163532	1.184682	0.335231	0.000000	
771	1.654549	1.277530	1.080058	1.587939	1.332435	1.045545	

raceId	241	242	243	244	245	246	\
driverId							
292	1.113651	1.079443	1.094318	1.041473	1.332580	0.984182	
475	5.506055	5.084942	3.525582	4.797775	1.325781	4.578594	
592	1.225570	1.195921	1.131532	1.124642	1.279515	1.057938	
94	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
771	1.320159	1.263417	1.220647	1.230118	1.316871	1.160095	

raceId	247	248	249	250	251	252	\
driverId							
292	1.257424	0.993279	0.983052	1.026934	1.096721	0.919417	
475	0.289527	2.124890	4.272615	4.606365	0.702221	2.890417	
592	1.190503	0.986409	1.072901	1.102054	1.079730	0.951714	
94	0.000000	0.000000	0.486145	0.179439	1.161675	0.138905	
771	1.199421	1.053958	1.130061	1.205421	1.079625	1.012256	

raceId	253	254	255	256	257	258	\
driverId							
292	1.086301	1.110775	0.989053	1.083664	0.991866	1.100497	
475	2.328131	4.330713	2.565573	4.181322	4.677814	2.473939	
592	1.071396	1.190237	1.020715	1.165657	1.061627	1.089945	
94	0.246758	0.143412	0.396085	0.827173	0.000000	0.000000	
771	1.147381	1.277072	1.083636	1.220730	1.170857	1.167001	

raceId	259	260	261	262	263	264	\
driverId							
292	0.893754	0.955893	0.995051	0.984304	0.910882	0.978784	
475	2.753531	2.534794	5.708493	4.922480	4.790133	5.044787	
592	0.928711	0.962851	1.121438	1.072035	1.001417	1.096475	
94	0.000000	0.000000	2.000000	0.000000	2.000000	0.000000	
771	0.999259	1.039752	1.222694	1.179806	1.107176	1.161289	

raceId	265	266	267	268	269	270	\
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driverId						
292	0.939964	0.862880	0.764148	1.238626	1.053752	0.851092
475	0.659794	4.772771	4.808606	6.896293	5.690191	5.007089
592	0.906135	0.959540	0.905621	1.388068	1.180127	0.968690
94	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
771	0.917624	1.060364	0.955760	1.512258	1.272577	1.067841

raceId	271	272	273	274	275	276	\
driverId							
292	0.877405	0.740111	0.764818	0.612179	0.612051	0.654614	
475	5.691409	0.514119	1.556572	3.363338	3.454241	1.641124	
592	1.002737	0.700209	0.801423	0.699102	0.707395	0.668865	
94	0.000000	0.000000	0.574779	0.243860	0.288738	0.219961	
771	1.106748	0.711513	0.819293	0.743164	0.751263	0.712858	

raceId	277	278	279	280	281	282	\
driverId							
292	0.596100	0.638945	0.600056	0.530887	0.639453	0.639014	
475	1.965584	3.640879	3.125748	3.850229	1.867235	1.881451	
592	0.634722	0.738878	0.658974	0.625689	0.659473	0.667885	
94	0.107123	0.342029	0.057199	0.036778	0.000000	0.000000	
771	0.674079	0.784469	0.729477	0.699454	0.707436	0.711312	

raceId	283	284	285	286	287	288	\
driverId							
292	0.844257	0.534863	0.908334	0.652571	0.452429	0.443698	
475	4.061927	4.872419	4.664161	3.245715	2.523616	3.463620	
592	0.912714	0.650541	0.997030	0.704696	0.523500	0.539377	
94	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
771	0.982099	0.740314	1.073185	0.779558	0.557920	0.591795	

raceId	289	290	291	292	293	294	\
driverId							
292	0.774599	0.816864	0.916301	0.905064	0.690120	0.450870	
475	1.370115	0.032821	0.993232	1.408044	0.146316	1.561823	
592	0.748921	0.743371	0.863746	0.868085	0.635048	0.470502	
94	0.000000	0.000000	0.000000	1.000000	1.000000	0.000000	
771	0.784096	0.764253	0.901160	0.918881	0.640773	0.496329	

raceId	295	296	297	298	299	300	\
driverId							
292	0.969639	0.835877	0.825350	0.599386	0.466092	0.788151	
475	2.382719	-0.335133	0.480865	1.291747	0.863658	2.758608	
592	0.981826	0.756488	0.765054	0.586742	0.474760	0.808422	
94	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
771	1.041314	0.757551	0.790670	0.620965	0.479119	0.884947	

raceId	301	302	303	304	305	306	\
driverId							
292	0.763098	0.723852	1.208414	1.197097	0.507604	0.582451	
475	5.447701	-0.183959	2.636881	4.154793	4.687691	3.879077	
592	0.895890	0.664117	1.212861	1.250467	0.636301	0.681407	
94	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
771	0.984656	0.664547	1.257418	1.338764	0.711888	0.738804	

raceId	307	308	309	310	311	312	\
driverId							
292	0.542552	0.548351	0.803782	0.696694	0.644537	0.695428	
475	2.575489	2.478938	3.597481	0.726535	1.129336	1.107582	
592	0.613027	0.595850	0.856542	0.667591	0.621746	0.666871	
94	3.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
771	0.639020	0.635316	0.921738	0.684333	0.663223	0.707137	

raceId	313	314	315	316	317	318	\
driverId							
292	0.840370	0.581082	0.604474	0.506462	0.706566	0.623902	
475	-0.282831	2.150856	4.004974	1.123492	2.922867	0.379219	
592	0.755830	0.615494	0.707624	0.497982	0.761029	0.578910	
94	0.000000	0.000000	0.000000	0.000000	3.000000	0.000000	
771	0.768805	0.646997	0.760627	0.528999	0.802929	0.604144	

raceId	319	320	321	322	323	324	\
driverId							
292	0.678360	0.257280	0.622972	0.677089	0.789859	0.694438	
475	2.318867	1.240113	3.893677	2.492245	1.827497	2.947935	
592	0.721025	0.280981	0.725128	0.716094	0.795212	0.768705	
94	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
771	0.754693	0.297393	0.774769	0.772782	0.834016	0.800485	

raceId	325	326	327	328	329	330	\
driverId							
292	0.590347	0.715671	0.688150	0.683549	0.664757	0.649327	
475	4.012520	1.287614	3.473902	3.199356	2.706760	3.231439	
592	0.680857	0.698440	0.761203	0.752355	0.732773	0.722336	
94	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
771	0.747674	0.747209	0.830354	0.814138	0.766917	0.766421	

raceId	331	332	333	334	335	336	\
driverId							
292	0.660094	0.646368	0.608033	0.707001	0.749203	0.723536	
475	3.705704	2.769662	1.746722	0.931721	3.600318	3.332477	
592	0.755624	0.707477	0.614138	0.680651	0.803204	0.754380	
94	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
771	0.813637	0.754104	0.657640	0.722029	0.868790	0.835126	

raceId	337	338	339	340	341	342	\
driverId							
292	5.366908	4.538896	2.887378	4.621794	3.240461	2.765328	
475	10.443079	10.690882	1.024504	7.428476	9.310629	2.234915	
592	5.434588	4.654449	2.805426	4.631480	3.422951	2.741937	
94	4.258396	3.378339	2.728648	3.794123	2.252733	2.681388	
771	5.589736	4.823972	2.791301	4.741446	3.545678	2.747736	

raceId	343	344	345	346	347	348	\
driverId							
292	3.820606	4.593097	5.339811	3.230824	4.962568	2.759503	
475	4.268626	5.503382	6.381233	1.570359	10.284758	6.608871	
592	3.766160	4.552255	5.270212	3.119848	5.068687	2.882333	
94	3.193169	4.171544	4.838177	2.636251	4.157130	2.215450	
771	3.842937	4.621511	5.339481	3.146728	5.204976	2.955037	

raceId	349	350	351	352	353	354	\
driverId							
292	2.822605	4.584574	4.242012	4.227160	5.255142	3.903331	
475	-0.169324	12.703785	10.710514	7.785535	11.309295	5.750564	
592	2.679510	4.788068	4.404249	4.298336	5.337141	3.927732	
94	2.770573	3.269319	3.041150	3.536939	4.037459	3.352840	
771	2.682728	4.968902	4.546761	4.384695	5.523644	3.985361	

raceId	355	356	357	358	359	360	\
driverId							
292	4.384551	0.600836	0.651485	0.719626	0.714614	0.650046	
475	4.024105	-0.066976	3.050882	3.167633	2.507364	1.632688	
592	4.306587	0.541799	0.731835	0.799920	0.772701	0.661504	
94	4.081249	0.000000	0.000000	0.000000	0.000000	0.000000	
771	4.340044	0.566461	0.776114	0.845738	0.801472	0.704907	

raceId	361	362	363	364	365	366	\
driverId							
292	0.657418	0.680614	0.618668	0.623317	0.622456	0.646440	
475	1.802451	1.142992	1.693306	3.239698	1.361844	2.604328	
592	0.671957	0.659247	0.616075	0.692929	0.618696	0.701757	
94	0.000000	0.000000	2.000000	0.000000	0.000000	0.000000	
771	0.702602	0.705331	0.672519	0.751136	0.652151	0.746206	

raceId	367	368	369	370	371	372	\
driverId							
292	0.705131	0.719614	0.817662	0.619437	0.658584	0.755552	
475	1.962957	1.405706	2.605378	1.398294	0.568204	2.983176	
592	0.726286	0.724071	0.856890	0.623711	0.643869	0.799818	
94	0.000000	2.000000	0.000000	0.409332	1.000000	0.168033	

771	0.774541	0.758110	0.902077	0.648254	0.649490	0.868291
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raceId	373	374	375	376	377	378	\
driverId							
292	0.687203	0.825871	0.768381	0.676397	0.691271	0.764679	
475	4.568082	1.595751	2.818020	4.233335	3.179158	3.467643	
592	0.804530	0.831564	0.827639	0.786573	0.773325	0.841302	
94	0.120172	0.376913	0.255993	0.166703	1.000000	0.000000	
771	0.878070	0.872634	0.879398	0.852829	0.819198	0.905159	

raceId	379	380	381	382	383	384	\
driverId							
292	0.673606	0.780711	0.735275	0.667464	1.067391	0.755447	
475	2.173488	3.140693	3.263987	4.055963	-0.349904	1.849177	
592	0.705479	0.857222	0.817185	0.770851	0.981055	0.776909	
94	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
771	0.737310	0.903138	0.865079	0.835590	0.987126	0.818940	

raceId	385	386	387	388	389	390	\
driverId							
292	0.692023	0.740589	0.660812	0.841124	0.784041	0.809321	
475	1.477245	3.266841	4.314061	3.891524	0.621592	1.791503	
592	0.689115	0.822295	0.762711	0.901399	0.751309	0.819048	
94	0.000000	0.000000	0.000000	0.147910	0.323780	0.384402	
771	0.735089	0.870409	0.843207	0.988704	0.765623	0.864357	

raceId	391	392	393	394	395	396	\
driverId							
292	0.857838	0.677830	0.590484	0.655906	0.809613	0.691986	
475	4.449904	4.726484	2.529428	2.239594	4.678571	5.456648	
592	0.961206	0.790352	0.607024	0.663383	0.903555	0.820020	
94	0.461221	0.039923	-0.186291	0.021932	0.374306	0.070184	
771	1.022009	0.869215	0.672118	0.713892	0.980050	0.914028	

raceId	397	398	399	400	401	402	\
driverId							
292	0.651594	0.687882	0.747119	0.625549	0.695238	0.997820	
475	2.057269	4.464560	3.146855	1.614076	1.494890	2.085219	
592	0.649366	0.775599	0.795133	0.614787	0.666003	1.024706	
94	-0.003410	0.069823	0.143537	-0.121059	0.075136	0.775580	
771	0.701798	0.853411	0.867034	0.667694	0.711926	1.046604	

raceId	403	404	405	406	407	408	\
driverId							
292	1.092152	0.559158	0.603414	0.617293	0.771654	0.785589	
475	0.020380	4.270443	2.028889	3.498345	2.155169	1.039950	
592	1.024198	0.654509	0.634711	0.677796	0.794640	0.767869	

94	0.770807	0.111026	0.036943	-0.039421	0.182294	0.303713
771	1.030091	0.724877	0.672022	0.758762	0.845316	0.788819

raceId	409	410	411	412	413	414	\
driverId							
292	0.626741	0.729929	0.686257	0.616780	0.569549	0.526948	
475	2.172295	2.515622	1.912392	2.188751	4.043886	3.932926	
592	0.632798	0.784688	0.677626	0.616562	0.645872	0.603646	
94	-0.146588	0.345366	-0.054903	-0.102273	-0.065844	-0.067148	
771	0.694516	0.818314	0.737209	0.679619	0.722318	0.675183	

raceId	415	416	417	418	419	420	\
driverId							
292	0.882914	0.664383	0.568928	0.687177	0.568612	1.020710	
475	1.934097	2.979335	2.229683	2.788045	3.455203	1.795384	
592	0.899906	0.687433	0.583926	0.733501	0.631154	1.025246	
94	0.499150	0.050381	-0.192925	0.109816	-0.046269	0.000000	
771	0.943129	0.755143	0.644035	0.790294	0.710484	1.066582	

raceId	421	422	423	424	425	426	\
driverId							
292	0.792983	0.906320	1.038053	1.220448	1.271700	0.862537	
475	1.458654	0.823664	1.733710	0.995181	1.122397	4.197716	
592	0.813296	0.880127	1.040435	1.187025	1.235560	0.926275	
94	0.000000	0.000000	0.657468	0.000000	0.000000	0.000000	
771	0.824167	0.894716	1.079945	1.208108	1.253457	1.012192	

raceId	427	428	429	430	431	432	\
driverId							
292	0.984763	1.036445	0.750040	0.507986	0.496219	0.507823	
475	2.839737	1.430511	2.579747	2.138672	3.840175	2.568842	
592	1.020141	1.030984	0.804584	0.552637	0.583299	0.557795	
94	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
771	1.078907	1.058501	0.851292	0.592953	0.663197	0.605826	

raceId	433	434	435	436	437	438	\
driverId							
292	0.611503	0.996937	1.221652	0.950056	0.601027	1.221409	
475	1.219253	0.212923	0.852540	1.829258	1.930605	0.669043	
592	0.605604	0.927082	1.182520	0.953643	0.627135	1.182811	
94	0.000000	0.000000	0.000000	0.486630	0.121803	1.143125	
771	0.635821	0.951155	1.192511	0.999858	0.668238	1.188748	

raceId	439	440	441	442	443	444	\
driverId							
292	0.977789	0.726441	0.427847	0.586484	0.699052	1.227400	
475	2.068172	0.623082	1.405566	4.316095	4.121826	1.016225	

592	0.989635	0.692595	0.454194	0.667196	0.773715	1.188575
94	0.549404	0.344684	0.199019	-0.069732	0.225682	1.061239
771	1.037988	0.711549	0.480622	0.756112	0.852839	1.205849

raceId	445	446	447	448	449	450	\
driverId							
292	0.644389	0.596516	0.573602	0.576821	0.809807	0.751809	
475	1.615783	1.511404	2.862306	1.452813	2.801914	3.024074	
592	0.667691	0.601613	0.620547	0.578892	0.876155	0.799110	
94	0.388084	0.000113	0.170280	-0.051715	0.000000	0.191173	
771	0.687685	0.647596	0.671801	0.625257	0.903776	0.866276	

raceId	451	452	453	454	455	456	\
driverId							
292	0.566319	0.552706	0.943495	0.725172	0.959206	0.828865	
475	2.855291	4.702940	1.984523	3.532052	1.002063	2.661119	
592	0.631103	0.664046	0.968558	0.781272	0.928597	0.846644	
94	0.023148	0.113899	0.735447	0.117951	0.628286	0.371766	
771	0.687573	0.739787	0.988440	0.861967	0.962009	0.908393	

raceId	457	458	459	460	461	462	\
driverId							
292	0.788566	1.123312	1.048797	0.600734	0.969012	0.713823	
475	2.516598	1.313714	0.207061	2.989901	0.747587	2.544588	
592	0.813968	1.099561	0.981979	0.637236	0.929474	0.734941	
94	0.265114	0.938679	0.883595	-0.088570	0.785251	0.118681	
771	0.876234	1.121334	0.999622	0.715951	0.951740	0.803515	

raceId	463	464	465	466	467	468	\
driverId							
292	1.043965	0.789143	0.500801	0.832450	0.801697	0.811649	
475	0.048983	2.970573	3.056018	1.594480	3.869513	1.480262	
592	0.978159	0.810892	0.536087	0.820775	0.889344	0.808756	
94	0.978447	0.437304	-0.147852	0.594396	0.259169	0.311066	
771	0.985674	0.875456	0.615199	0.853712	0.957721	0.849985	

raceId	469	470	471	472	473	474	\
driverId							
292	0.761616	1.961241	0.873827	0.748902	1.031683	0.743757	
475	2.821616	4.188713	1.033082	0.357728	0.859480	3.449619	
592	0.824572	2.017677	0.851425	0.708604	1.006109	0.791094	
94	0.411717	1.772289	0.707419	0.580256	0.957441	0.363267	
771	0.857170	2.057482	0.871552	0.718529	1.015231	0.856027	

raceId	475	476	477	478	479	480	\
driverId							
292	0.773264	0.841564	0.998357	0.867508	1.028988	0.797213	

475	3.275927	3.527561	1.955093	-1.513319	1.968784	3.208201
592	0.825510	0.930204	1.007426	0.750897	1.044680	0.850568
94	0.412852	0.482787	0.771785	0.952825	0.846584	0.247692
771	0.880510	0.970843	1.047539	0.742506	1.067858	0.913438

raceId	481	482	483	484	485	486	\
driverId							
292	1.066254	1.011566	0.683131	0.772936	0.478162	0.496812	
475	0.308753	0.834629	4.309421	4.157916	4.885783	3.239125	
592	1.010901	0.989741	0.794699	0.887409	0.594546	0.551097	
94	0.987717	0.865004	0.344292	0.446149	-0.101257	0.084420	
771	1.021305	1.002439	0.852645	0.931946	0.684119	0.613434	

raceId	487	488	489	490	491	492	\
driverId							
292	0.842480	0.894935	0.955861	0.674599	0.845693	0.503366	
475	3.552492	1.765255	1.772859	2.741071	2.242906	3.536746	
592	0.929571	0.925706	0.982220	0.714179	0.884832	0.568746	
94	0.413240	0.889874	0.844053	0.166446	0.646831	-0.050235	
771	0.966617	0.935158	0.991190	0.778484	0.906665	0.645989	

raceId	493	494	495	496	497	498	\
driverId							
292	0.838336	0.525324	0.691516	0.866519	0.647772	0.511072	
475	2.412607	4.053540	4.794073	1.488114	3.596980	2.877621	
592	0.865731	0.617273	0.823668	0.877288	0.733113	0.570380	
94	0.672689	-0.103988	0.082940	0.766886	0.122310	0.310715	
771	0.902517	0.701235	0.900702	0.889877	0.794144	0.618035	

raceId	499	500	501	502	503	504	\
driverId							
292	0.626109	0.725841	0.728025	0.701711	0.774324	0.605330	
475	0.570635	1.116073	3.554170	1.951340	3.673297	2.725910	
592	0.616289	0.720050	0.764380	0.744803	0.849042	0.676077	
94	0.883297	0.877569	-0.192549	0.910418	0.356249	0.769251	
771	0.621127	0.734618	0.854126	0.758828	0.902593	0.704323	

raceId	505	506	507	508	509	510	\
driverId							
292	0.488171	0.807233	0.845945	0.564937	0.558036	0.712004	
475	3.993898	3.704265	2.653087	2.925910	4.184518	3.106588	
592	0.592022	0.895562	0.890778	0.606983	0.649186	0.800300	
94	0.253887	0.603392	0.657984	0.259832	0.154618	0.815755	
771	0.651405	0.939574	0.924062	0.664770	0.720531	0.826586	

raceId	511	512	513	514	515	516	\
driverId							

292	0.728899	0.905750	0.916816	0.856814	0.840763	0.737749
475	3.444972	1.522083	1.524575	1.729643	2.170774	2.307217
592	0.826170	0.918358	0.935017	0.887871	0.893679	0.788902
94	0.755565	0.946000	1.009181	0.744197	0.800141	0.572322
771	0.858651	0.925396	0.938626	0.905931	0.915324	0.816442

raceId	517	518	519	520	521	522	\
driverId							
292	0.690345	0.645563	0.903349	0.866014	0.665041	0.747867	
475	2.904718	3.328636	-0.051371	0.926961	2.853898	2.448160	
592	0.768679	0.738095	0.862272	0.850835	0.748956	0.821463	
94	0.502676	0.303920	1.101171	0.744585	0.679387	0.931379	
771	0.807054	0.789670	0.847271	0.865718	0.776791	0.835246	

raceId	523	524	525	526	527	528	\
driverId							
292	0.488416	0.720940	0.657435	0.727646	0.789933	0.617434	
475	3.946638	2.981339	2.576728	-1.027366	2.074724	3.964652	
592	0.613959	0.802746	0.737631	0.669285	0.809688	0.690300	
94	0.375690	0.318547	0.767518	1.258729	0.202037	-0.036254	
771	0.666082	0.848721	0.757752	0.634870	0.851829	0.770970	

raceId	529	530	531	532	533	534	\
driverId							
292	0.609152	0.625982	0.699925	0.652268	0.669410	0.659765	
475	2.443740	2.994145	1.893430	1.936290	1.878025	2.854796	
592	0.670218	0.690238	0.735860	0.692211	0.707609	0.703777	
94	0.604912	0.437960	0.250852	0.600672	0.503565	-0.010078	
771	0.697235	0.731820	0.765601	0.713133	0.734118	0.760489	

raceId	535	536	537	538	539	540	\
driverId							
292	0.690291	0.567422	0.722115	0.676210	0.672840	0.643815	
475	2.323053	3.094957	1.898086	1.768810	2.005272	2.073156	
592	0.728828	0.632498	0.752702	0.711388	0.707206	0.678368	
94	0.403870	0.121362	0.357704	0.654766	0.317556	0.170100	
771	0.770133	0.679938	0.790675	0.731507	0.742025	0.708577	

raceId	541	542	543	544	545	546	\
driverId							
292	0.510037	0.812166	0.753658	0.772895	0.580034	0.822160	
475	5.279709	1.929700	3.498221	4.788420	3.141604	2.049352	
592	0.656641	0.851897	0.834597	0.847725	0.650213	0.850416	
94	0.210927	0.748712	0.316699	-0.023509	-0.259580	0.206276	
771	0.738821	0.870387	0.898516	0.946944	0.714253	0.892525	

raceId	547	548	549	550	551	552	\
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driverId						
292	0.660206	0.457223	0.600209	0.822894	0.857193	0.653618
475	2.049978	3.700877	1.946548	0.843239	0.991791	2.282961
592	0.697756	0.565915	0.631275	0.813435	0.835534	0.662712
94	0.385935	-0.193144	0.276520	0.860727	0.503708	-0.084231
771	0.729923	0.630411	0.660737	0.812236	0.857851	0.720681

raceId	553	554	555	556	557	558	\
driverId							
292	0.483652	0.525071	0.544990	0.580802	0.753630	0.680448	
475	3.257402	3.760846	3.131719	2.150123	3.187754	3.053694	
592	0.568461	0.620525	0.615535	0.625006	0.792786	0.762691	
94	-0.233606	0.160363	-0.161901	0.141964	-0.061270	0.095566	
771	0.627286	0.675975	0.676126	0.660651	0.869585	0.813745	

raceId	559	560	561	562	563	564	\
driverId							
292	0.868355	0.756576	0.702181	0.776893	0.710049	0.581261	
475	5.050161	1.656303	2.753690	1.960193	3.217705	3.082110	
592	0.954971	0.773581	0.732581	0.796030	0.737234	0.653423	
94	-0.082127	0.182992	-0.224330	0.280218	-0.135455	-0.055380	
771	1.053818	0.801800	0.799395	0.831352	0.814331	0.706544	

raceId	565	566	567	568	569	570	\
driverId							
292	0.662489	0.577881	0.875155	0.539135	0.801562	1.116996	
475	2.762787	2.815717	1.484827	3.006217	2.289891	0.509402	
592	0.724629	0.654088	0.854680	0.614414	0.811573	1.069364	
94	-0.097335	0.040750	0.401638	-0.152376	0.190074	1.011026	
771	0.777819	0.703300	0.895043	0.670134	0.870959	1.073352	

raceId	571	572	573	574	575	576	\
driverId							
292	0.965214	0.565358	0.840912	0.687239	0.917294	0.926483	
475	3.715957	3.310760	2.138449	3.248689	1.716060	3.683743	
592	1.002429	0.651624	0.846913	0.733181	0.919921	0.947480	
94	-0.130481	0.282536	0.259930	-0.155817	0.618186	0.071200	
771	1.090762	0.701136	0.899988	0.810423	0.950870	1.045612	

raceId	577	578	579	580	581	582	\
driverId							
292	0.964422	0.000000	0.496787	0.574759	0.545319	0.638307	
475	1.251953	3.986814	0.225688	3.359761	3.891742	3.500808	
592	0.928721	0.618495	0.474548	0.632755	0.648412	0.708443	
94	0.463812	0.079336	0.472709	-0.257570	-0.240097	-0.046315	
771	0.970815	0.679544	0.475837	0.710777	0.717575	0.769523	

raceId	583	584	585	586	587	588	\
driverId							
292	0.792728	0.786790	0.838878	0.643251	0.410744	0.750402	
475	3.541837	2.973118	2.413431	3.256820	0.381630	3.592675	
592	0.826384	0.806927	0.841814	0.710706	0.391162	0.795142	
94	-0.112047	-0.221630	0.167209	0.376780	0.256739	-0.033728	
771	0.909656	0.884610	0.915407	0.754101	0.402330	0.879740	

raceId	589	590	591	592	593	594	\
driverId							
292	0.708339	0.672153	0.931737	0.000000	0.526161	0.589457	
475	3.375633	2.934824	1.399337	2.212960	3.270087	3.350902	
592	0.747367	0.711693	0.904065	0.749078	0.587731	0.642759	
94	-0.313668	0.134362	0.470677	0.729836	-0.358750	-0.379549	
771	0.834483	0.770710	0.950527	0.768234	0.664183	0.732441	

raceId	595	596	597	598	599	600	\
driverId							
292	0.711424	0.751328	0.567659	0.513002	0.694043	0.595006	
475	3.482588	2.506312	3.170215	4.608686	3.480050	3.791899	
592	0.806502	0.796165	0.626385	0.644545	0.767847	0.700200	
94	0.485487	0.191252	-0.299317	0.020589	-0.011724	0.285450	
771	0.857559	0.850792	0.700024	0.718668	0.845203	0.757973	

raceId	601	602	603	604	605	606	\
driverId							
292	0.538737	0.676855	0.740163	0.611205	1.018526	0.902812	
475	3.845580	3.407556	2.792675	3.049420	1.997372	2.186745	
592	0.612163	0.751046	0.762102	0.659336	1.002445	0.891982	
94	0.196650	0.297444	0.124524	0.249598	0.405511	0.233024	
771	0.679991	0.816207	0.836081	0.716891	1.064623	0.961991	

raceId	607	608	609	610	611	612	\
driverId							
292	0.000000	1.151984	0.638772	0.614449	0.857300	0.638754	
475	2.096542	0.819663	2.589032	3.436929	4.515325	4.324614	
592	0.594199	1.092873	0.679068	0.691770	0.948073	0.752678	
94	-0.086236	0.722780	-0.064106	0.026141	0.525572	0.410045	
771	0.660610	1.129537	0.743361	0.765456	1.022346	0.815371	

raceId	613	614	615	616	617	618	\
driverId							
292	0.694666	0.562282	0.736980	0.727112	0.790289	0.938716	
475	2.858101	2.732742	2.623096	4.772018	3.529559	0.557660	
592	0.738959	0.612990	0.780591	0.864026	0.871103	0.890202	
94	0.485518	-0.056234	0.175884	0.391221	0.504214	0.658867	
771	0.789126	0.675736	0.837883	0.931616	0.930986	0.914832	

raceId	619	620	621	622	623	624	\
driverId							
292	0.646766	0.703921	0.965837	1.023422	0.989183	1.072882	
475	4.087451	3.493554	2.057072	0.177781	1.130700	2.907162	
592	0.732285	0.763128	0.945471	0.948141	0.961133	1.075336	
94	0.389060	0.110172	0.538653	0.677970	0.655384	0.215398	
771	0.800118	0.837494	1.001727	0.975636	0.992859	1.161055	

raceId	625	626	627	628	629	630	\
driverId							
292	0.762029	0.928567	1.021854	1.080991	1.003885	0.604366	
475	2.868175	1.952596	1.826575	1.116006	0.622805	3.783251	
592	0.801138	0.913070	1.033927	1.018709	0.931774	0.682527	
94	0.081755	0.271525	0.959128	0.622111	0.577990	0.014610	
771	0.873541	0.977743	1.056362	1.066599	0.969505	0.759352	

raceId	631	632	633	634	635	636	\
driverId							
292	0.389692	0.841209	0.856836	0.742037	1.211543	0.749911	
475	3.580741	2.417662	3.548075	5.732254	1.257042	2.899243	
592	0.465230	0.878959	0.912326	0.880689	1.183299	0.790559	
94	-0.235428	0.315837	0.163325	0.023000	1.160557	-0.093604	
771	0.543647	0.923818	0.985643	0.985070	1.207362	0.862573	

raceId	637	638	639	640	641	642	\
driverId							
292	0.760517	0.716605	1.270723	0.988398	0.549060	0.701023	
475	4.510627	4.925452	-1.562743	3.158545	5.980992	2.617975	
592	0.866978	0.840923	1.139359	1.048969	0.713392	0.760694	
94	0.098330	-0.116954	1.079905	0.913592	-0.170624	0.417617	
771	0.950820	0.929363	1.127536	1.086878	0.815605	0.798232	

raceId	643	644	645	646	647	648	\
driverId							
292	0.919581	0.939850	1.126030	1.425949	0.974024	1.066216	
475	4.733098	3.779654	1.150037	-0.606072	2.758838	0.613115	
592	0.995795	1.004931	1.078765	1.331050	0.995814	1.008907	
94	0.296222	0.009276	0.882733	1.374690	0.405756	0.912212	
771	1.091667	1.082797	1.111115	1.320358	1.057170	1.032345	

raceId	649	650	651	652	653	654	\
driverId							
292	0.953479	0.927200	1.095623	0.766066	1.329502	0.971013	
475	1.923237	0.583593	1.270383	3.761178	0.330595	-2.124341	
592	0.946457	0.879148	1.083741	0.841587	1.266847	0.834923	
94	0.766432	0.811533	1.032321	0.123158	1.250188	0.911910	

771	0.983571	0.897579	1.095770	0.909269	1.274057	0.820865
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raceId	655	656	657	658	659	660	\
driverId							
292	1.361229	1.101899	1.304208	1.571474	1.250068	1.507943	
475	2.686833	4.694249	5.077268	0.435138	3.556130	4.947858	
592	1.379218	1.175275	1.393417	1.496382	1.286323	1.583276	
94	1.254502	0.065812	0.389415	1.253343	0.440731	0.627569	
771	1.413276	1.265602	1.488371	1.494163	1.362905	1.675668	

raceId	661	662	663	664	665	666	\
driverId							
292	1.313041	1.570011	1.267832	1.222708	1.291600	1.225203	
475	4.551713	3.380474	3.810155	1.773693	0.963108	4.500520	
592	1.378788	1.582971	1.321484	1.205206	1.255372	1.282421	
94	0.466533	0.873391	0.485700	1.084838	1.309264	0.720259	
771	1.474393	1.650925	1.396247	1.241961	1.266231	1.367993	

raceId	667	668	669	670	671	672	\
driverId							
292	0.832404	1.668383	1.342050	1.303096	1.045454	1.259387	
475	3.555233	4.613730	2.556865	0.953516	3.643392	3.579141	
592	0.894909	1.709556	1.341713	1.264200	1.106193	1.309441	
94	0.337579	0.747870	0.731682	0.945090	0.320814	0.894294	
771	0.947433	1.786613	1.380460	1.287890	1.176770	1.364878	

raceId	673	674	675	676	677	678	\
driverId							
292	1.137629	1.080293	1.027760	1.160058	1.045848	1.252358	
475	0.576457	4.337587	2.828615	2.683236	4.375128	0.243191	
592	1.090211	1.147289	1.052001	1.165553	1.123053	1.186344	
94	0.987850	0.152662	0.814362	0.717540	0.112060	0.911332	
771	1.102073	1.233206	1.097136	1.215243	1.200930	1.185960	

raceId	679	680	681	682	683	684	\
driverId							
292	1.438725	1.299450	0.961844	1.242912	1.449806	0.892132	
475	1.174007	1.511956	4.882833	0.951610	3.050429	4.769753	
592	1.400491	1.256156	1.054819	1.204489	1.446145	0.986044	
94	1.362579	0.982379	0.495953	0.777128	1.032504	0.447385	
771	1.415007	1.283218	1.139320	1.231989	1.514682	1.065746	

raceId	685	686	687	688	689	690	\
driverId							
292	0.959796	1.484393	1.141076	0.980915	0.954331	1.109881	
475	2.729907	2.555209	3.690248	3.954972	5.232744	0.650300	
592	0.974306	1.463091	1.202186	1.043577	1.061762	1.063272	

94	0.782602	1.207165	0.966439	0.438094	0.529718	0.525361
771	1.026343	1.513989	1.254108	1.104298	1.148180	1.087687

raceId	691	692	693	694	695	696	\
driverId							
292	1.402700	1.562290	1.231314	1.245204	1.349745	1.076481	
475	2.065613	6.357414	3.526746	2.871260	2.286313	1.188549	
592	1.400351	1.656542	1.249582	1.250309	1.336919	1.053471	
94	1.386744	0.535293	0.820974	0.682193	1.072276	0.973572	
771	1.423846	1.790990	1.320022	1.310806	1.383137	1.070967	

raceId	697	698	699	700	701	702	\
driverId							
292	0.881583	1.347313	0.607334	1.445031	0.777845	0.852437	
475	3.817083	3.043194	4.176164	2.317420	4.367281	4.847257	
592	0.964322	1.368437	0.710019	1.437547	0.863993	0.955621	
94	0.540080	1.243541	0.160212	0.807118	0.007234	0.157392	
771	1.018040	1.412280	0.767228	1.470848	0.949699	1.039683	

raceId	703	704	705	706	707	708	\
driverId							
292	0.731518	0.858562	0.925450	0.900823	1.577341	1.334887	
475	3.680842	4.051253	3.449186	0.235642	1.024911	1.332503	
592	0.812002	0.935076	0.981699	0.850359	1.511145	1.311090	
94	0.216512	0.111894	0.417339	0.283701	1.254429	1.222360	
771	0.861836	1.008550	1.032537	0.867697	1.524572	1.323880	

raceId	709	710	711	712	713	714	\
driverId							
292	1.073142	1.016365	1.052321	1.486870	0.927799	1.150183	
475	1.813851	4.542096	4.800002	0.977466	4.709027	0.898433	
592	1.065768	1.107477	1.133965	1.426767	1.016645	1.120949	
94	0.617507	0.298956	0.057265	1.125362	0.087850	1.106958	
771	1.089511	1.181250	1.235353	1.444746	1.101118	1.116550	

raceId	715	716	717	718	719	720	\
driverId							
292	1.187861	1.063638	1.343092	1.253892	1.112799	0.890606	
475	0.703594	1.747469	0.814322	1.667348	0.885861	4.124736	
592	1.152348	1.069857	1.295561	1.248877	1.074276	0.970265	
94	1.145688	0.992777	1.186333	1.052597	0.826196	-0.025299	
771	1.155465	1.087744	1.291520	1.266394	1.080719	1.055962	

raceId	721	722	723	724	725	726	\
driverId							
292	0.981272	0.700888	0.904888	0.758059	0.721219	1.037905	
475	4.417879	4.275589	4.660744	4.059740	4.602994	2.420875	

592	1.071173	0.789692	1.003866	0.853269	0.819709	1.042671
94	0.233201	-0.105307	0.165991	0.369501	-0.144307	0.456673
771	1.149482	0.878329	1.079705	0.912605	0.914932	1.085923

raceId	727	728	729	730	731	732	\
driverId							
292	0.861448	0.886682	1.191008	1.049771	0.827931	1.221184	
475	4.977984	3.563834	0.236867	1.309631	4.593893	0.936958	
592	0.954388	0.945796	1.128339	1.034170	0.919862	1.187214	
94	-0.048165	-0.037657	1.026214	0.815965	-0.023286	1.021724	
771	1.056995	1.017593	1.121510	1.057400	1.002621	1.201591	

raceId	733	734	735	736	737	738	\
driverId							
292	0.889761	0.875052	0.824908	1.067117	1.323752	0.978645	
475	4.770740	1.639897	-0.035501	4.259405	0.341286	9.000000	
592	0.987035	0.875025	0.774800	1.128514	1.246201	1.022406	
94	0.048141	0.439542	0.566519	0.045291	0.895005	0.697812	
771	1.075294	0.894982	0.766449	1.217272	1.258395	1.069388	

raceId	739	740	741	742	743	744	\
driverId							
292	1.064199	0.882871	0.762438	0.724154	0.531126	0.678269	
475	3.000000	0.000000	0.000000	0.000000	9.000000	0.000000	
592	1.122064	0.901951	0.751850	0.744863	0.628425	0.663375	
94	0.617847	0.828237	0.370063	0.612194	0.098546	0.540586	
771	1.187074	0.929626	0.774441	0.781462	0.695054	0.679282	

raceId	745	746	747	748	749	750	\
driverId							
292	1.362496	0.898525	0.883107	0.714739	1.120596	1.140027	
475	0.000000	0.000000	8.000000	2.213715	3.000000	0.000000	
592	1.290121	0.862490	1.009785	0.740625	1.101155	1.129112	
94	1.189842	0.627893	-0.144584	0.363277	0.848466	0.719843	
771	1.291120	0.876140	1.122236	0.782580	1.143080	1.187778	

raceId	751	752	753	754	755	756	\
driverId							
292	0.943166	1.003077	1.292279	1.477574	0.903486	1.071282	
475	2.403377	2.212224	0.000000	5.128975	8.000000	0.000000	
592	0.949080	1.004772	1.288871	1.549306	0.920882	1.059041	
94	0.500344	0.832522	0.702424	0.826376	0.590743	0.737234	
771	1.010240	1.050805	1.358829	1.643589	0.967303	1.116177	

raceId	757	758	759	760	761	762	\
driverId							
292	0.715813	1.410928	1.115746	0.892969	1.594267	1.294349	

475	2.058676	1.000000	1.000000	6.500000	0.000000	9.000000
592	0.737301	1.373881	1.144317	1.018497	1.530292	1.393306
94	0.394078	1.287717	0.696286	-0.173567	1.601742	0.460056
771	0.775925	1.400460	1.207727	1.154285	1.530421	1.484785

raceId	763	764	765	766	767	768	\
driverId							
292	1.078137	1.256511	2.070227	0.833142	1.157997	0.708649	
475	8.000000	0.000000	8.000000	0.000000	9.000000	2.001942	
592	1.234156	1.192588	2.127301	0.792535	1.269826	0.000000	
94	0.039228	0.964312	1.303681	0.781550	0.323670	0.373380	
771	1.369417	1.212679	2.226387	0.803884	1.365520	0.766469	

raceId	769	770	771	772	773	774	\
driverId							
292	1.231466	0.775987	1.160154	0.857136	1.303867	0.991053	
475	0.000000	6.000000	0.000000	1.000000	8.000000	0.000000	
592	1.231093	0.872658	1.147092	0.816956	1.442990	0.999185	
94	0.881289	0.209242	0.953254	0.949365	0.172678	0.742822	
771	1.267773	0.948537	1.169874	0.811768	1.567506	1.033047	

raceId	775	776	777	778	779	780	\
driverId							
292	0.708132	1.113935	0.983586	0.711694	1.381572	1.026794	
475	9.000000	1.000000	0.000000	2.762620	4.408575	2.500000	
592	0.885318	1.108748	0.996201	0.000000	1.442512	1.023283	
94	-0.300455	0.491189	0.276254	0.252626	0.538212	0.841788	
771	1.009821	1.145360	1.044075	0.806855	1.521088	1.046823	

raceId	781	782	783	784	785	786	\
driverId							
292	0.800711	1.223862	0.917573	1.378599	0.902675	0.690098	
475	2.000000	9.000000	8.000000	0.000000	8.000000	1.543299	
592	0.881653	1.322469	1.022011	1.342902	0.974891	0.000000	
94	-0.075670	0.426898	0.160101	1.074554	0.396652	0.432578	
771	0.962644	1.410171	1.113982	1.365695	1.042812	0.726428	

raceId	787	788	789	790	791	792	\
driverId							
292	1.582358	1.189454	0.591468	0.901850	0.760176	0.394456	
475	1.500000	0.500000	1.000000	6.000000	9.000000	0.500000	
592	1.541802	1.164420	0.612511	1.006936	0.838382	0.410671	
94	1.425713	0.819933	0.009778	-0.052083	0.348533	-0.203263	
771	1.561958	1.187737	0.649679	1.105219	0.904247	0.441990	

raceId	793	794	795	796	797	798	\
driverId							

292	0.963974	0.667232	0.771097	1.099216	0.607722	0.681864
475	0.000000	1.072351	6.000000	6.000000	9.000000	1.000000
592	0.924259	0.000000	0.865631	1.184051	0.728804	0.703103
94	0.800647	0.489401	-0.080458	0.240205	-0.149723	0.040874
771	0.936705	0.681657	0.952377	1.274815	0.815881	0.743188

raceId	799	800	801	802	803	804	\
driverId							
292	0.842007	0.523768	1.097243	0.842510	0.554119	0.633494	
475	4.717050	1.648736	4.000000	1.540113	0.000000	0.000000	
592	0.936721	0.000000	1.119015	0.844354	0.582230	0.667660	
94	-0.042838	0.245463	0.383529	0.284686	0.127235	-0.032971	
771	1.030231	0.574806	1.173860	0.875835	0.624474	0.720226	

raceId	805	806	807	808	809	810	\
driverId							
292	0.909288	0.680346	0.893516	1.052521	0.574582	0.878794	
475	0.000000	0.000000	0.000000	4.409565	1.486469	0.000000	
592	0.953025	0.685858	0.905841	1.126853	0.586964	0.935282	
94	0.100917	0.094216	0.437784	0.646247	0.325760	0.492592	
771	1.018211	0.720195	0.948193	1.203534	0.614717	1.001889	

raceId	811	812	813	814	815	816	\
driverId							
292	1.020577	0.564217	0.426847	0.463374	0.750295	0.549220	
475	3.288256	0.000000	4.885539	0.000000	5.155221	0.000000	
592	1.062515	0.616546	0.550104	0.506436	0.862823	0.584819	
94	0.727535	-0.104290	-0.332446	-0.118610	0.197188	-0.165148	
771	1.118881	0.676060	0.644632	0.558160	0.957890	0.637098	

raceId	817	818	819	820	821	822	\
driverId							
292	1.139137	0.752334	0.729274	0.916160	0.527317	0.533066	
475	0.000000	0.664835	0.000000	6.121274	0.000000	6.507200	
592	1.116876	0.000000	0.825618	1.048117	0.617418	0.697099	
94	0.772098	0.649712	-0.133998	-0.201231	-0.289961	-0.655579	
771	1.140842	0.741438	0.920835	1.168711	0.699823	0.827169	

raceId	823	824	825	826	827	828	\
driverId							
292	0.887026	0.369004	0.713884	0.688204	1.629828	0.602509	
475	0.000000	0.000000	0.000000	1.371187	4.758379	2.173158	
592	0.983383	0.472279	0.717795	0.691617	1.682425	0.634732	
94	-0.040821	-0.417901	0.053529	0.459262	1.101658	0.252707	
771	1.083921	0.558701	0.752202	0.000000	1.767410	0.675409	

raceId	829	830	831	832	833	834	\
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driverId						
292	0.818199	0.585289	0.721896	0.633457	1.011377	0.661811
475	2.574507	4.470791	4.397810	3.761533	4.272034	2.955703
592	0.851432	0.688127	0.813766	0.712744	1.081772	0.716506
94	0.227887	-0.174233	0.275898	-0.190122	0.535493	-0.037718
771	0.901729	0.773761	0.892636	0.788540	1.161410	0.774292

raceId	835	836	837	838	839	841	\
driverId							
292	0.676233	1.294925	1.231087	0.912767	0.708619	4.183991	
475	1.130270	2.629335	3.389405	3.079443	2.790181	4.301316	
592	0.673509	1.301613	1.266067	0.956342	0.752292	4.141209	
94	0.489056	0.964906	0.462857	0.172984	0.386126	4.119024	
771	0.000000	1.349487	1.332392	1.017043	0.804551	4.168907	

raceId	842	843	844	845	846	847	\
driverId							
292	4.343833	4.253297	4.088117	4.649190	4.354845	3.640585	
475	8.278460	2.681970	5.204434	6.026908	8.587025	8.674244	
592	4.423168	4.144227	4.083311	4.631805	4.449846	3.761911	
94	3.756069	4.078895	3.628831	4.141831	3.761499	2.697080	
771	4.511230	4.165606	4.129693	4.695828	4.540930	3.874561	

raceId	848	849	850	851	852	853	\
driverId							
292	4.311331	4.504277	3.998830	4.403547	3.683452	5.285734	
475	6.476421	8.148155	3.940314	8.605036	8.341236	10.188485	
592	4.342343	4.568200	3.948091	4.494919	3.807919	5.364208	
94	3.905312	3.775159	3.794435	3.839287	2.774073	4.482442	
771	4.404705	4.670461	3.991728	4.595941	3.906144	5.490277	

raceId	854	855	856	857	858	859	\
driverId							
292	4.197889	4.574606	4.410197	4.430570	4.162721	3.042350	
475	6.923591	10.815598	4.757133	9.259159	6.486780	6.961126	
592	4.246650	4.727172	4.373469	4.536767	4.177655	3.166115	
94	3.656761	3.665768	4.224910	3.469802	3.586719	2.408063	
771	4.316654	4.870756	4.408983	4.650642	4.277469	3.242156	

raceId	860	861	862	863	864	865	\
driverId							
292	4.169225	4.611964	3.567076	3.685094	4.081628	2.859251	
475	6.820635	10.471679	2.728462	4.775996	9.107001	3.355757	
592	4.207661	4.711266	3.470947	3.661135	4.153612	2.854913	
94	3.766500	3.415391	2.876458	2.988218	2.932419	2.313369	
771	4.283676	4.877835	3.513171	3.708048	4.288797	2.895003	

raceId	866	867	868	869	870	871	\
driverId							
292	5.099124	3.667856	2.874136	4.405784	5.333727	3.463968	
475	5.071253	12.265410	6.824604	13.451855	6.855106	7.744797	
592	4.984203	3.883588	3.000946	4.631150	5.274167	3.562468	
94	4.498198	1.921509	2.339651	3.017527	4.696303	2.761080	
771	5.055331	4.084423	3.077855	4.827847	5.361736	3.657637	

raceId	872	873	874	875	876	877	\
driverId							
292	6.180662	3.991308	4.413682	2.848562	3.776296	4.706244	
475	10.349033	7.950914	5.148753	5.160163	5.829385	11.947991	
592	6.156483	4.063657	4.362210	2.922804	3.823550	4.853461	
94	4.820450	3.223725	4.156644	2.640496	3.642735	3.453686	
771	6.334879	4.159398	4.409831	2.960537	3.870758	5.019182	

raceId	878	879	880	881	882	883	\
driverId							
292	5.415893	2.845873	5.283611	3.613779	5.861541	4.807935	
475	6.798025	9.524014	9.540038	1.818368	10.925430	6.158094	
592	5.367633	3.063101	5.321080	3.509953	5.909798	4.750189	
94	5.118793	2.219341	4.249498	3.427026	4.783031	4.058230	
771	5.444510	3.189300	5.450516	3.508558	6.065920	4.820010	

raceId	884	885	886	887	888	890	\
driverId							
292	4.954310	3.473017	3.872787	4.437799	4.796958	5.258731	
475	10.895209	3.168369	3.854283	7.792413	6.849899	6.747690	
592	5.053812	3.408467	3.828702	4.447130	4.780918	5.213062	
94	3.529195	2.715364	3.627347	2.767435	4.194665	4.673000	
771	5.218177	3.451727	3.858380	4.593262	4.853125	5.293913	

raceId	891	892	893	894	895	896	\
driverId							
292	4.096495	2.966719	5.608082	4.790768	2.672247	4.760478	
475	4.379861	3.516666	8.622718	6.077155	3.269922	5.098300	
592	4.060739	2.972254	5.594348	4.737921	2.680287	4.660167	
94	3.855741	2.807115	4.615857	4.167862	2.457574	3.909677	
771	4.097159	2.993648	5.707976	4.802387	2.692535	4.727074	

raceId	897	898	899	900	901	902	\
driverId							
292	3.024811	4.206877	4.692567	3.495805	4.533380	5.536478	
475	2.476184	4.195848	8.082601	6.586228	3.856850	5.722101	
592	2.978709	4.145813	4.734159	3.523549	4.448944	5.398996	
94	2.662567	3.897056	3.682741	1.858638	3.978801	4.311635	
771	2.991503	4.174835	4.836056	3.652016	4.497442	5.508558	

raceId	903	904	905	906	907	908	\
driverId							
292	5.013214	5.092618	4.505289	3.001609	5.132125	4.159788	
475	4.920542	3.677727	6.497154	3.170363	5.765657	1.752851	
592	4.910499	4.930041	4.486564	2.971425	5.015485	3.997268	
94	4.017436	4.165550	3.027780	2.074232	3.661415	4.124302	
771	4.993167	4.993714	4.611412	3.021407	5.138568	4.013924	

raceId	909	910	911	912	913	914	\
driverId							
292	4.072425	4.939065	4.355166	5.330346	4.903605	4.552302	
475	1.990722	7.102016	5.384028	4.014778	4.943084	2.170901	
592	3.921336	4.908238	4.269780	5.153606	4.819170	4.389873	
94	3.173776	3.708144	2.825477	4.413714	4.643117	4.003112	
771	3.962006	5.029640	4.374748	5.230146	4.875093	4.420078	

raceId	915	916	917	918	926	927	\
driverId							
292	4.797651	4.962828	5.148323	10.281156	4.942573	4.746946	
475	4.016283	3.920014	6.896573	8.946795	3.885317	2.756292	
592	4.662780	4.818231	5.112821	9.978376	4.815272	4.586375	
94	3.863893	4.062742	3.861368	9.466413	4.345481	4.195550	
771	4.739521	4.892531	5.226062	10.124961	4.868404	4.611708	

raceId	928	929	930	931	932	933	\
driverId							
292	4.863879	5.012923	4.910015	4.859207	4.793040	4.571399	
475	3.036107	3.808423	3.142811	4.636573	2.725427	2.504414	
592	4.701646	4.849557	4.735959	4.741528	4.610642	4.392136	
94	4.158940	3.987257	3.837459	3.625818	3.971468	3.722617	
771	4.743326	4.916092	4.791730	4.817688	4.658854	4.440439	

raceId	934	936	937	938	939	940	\
driverId							
292	4.640436	3.381563	4.810984	4.206961	3.907836	4.728622	
475	2.131418	2.321305	5.181304	1.895546	3.489278	2.630422	
592	4.463399	3.296436	4.692945	4.057087	3.805852	4.553669	
94	4.129958	3.324662	3.682993	4.203608	2.981144	3.968334	
771	4.490883	3.300140	4.791900	4.064831	3.851607	4.591989	

raceId	941	942	943	944	945	948	\
driverId							
292	4.181935	5.242695	4.526668	4.706463	5.309690	4.530112	
475	3.618072	4.926786	3.045174	3.096467	5.884274	2.514663	
592	4.092682	5.103518	4.345465	4.540925	5.192474	4.364348	
94	4.106055	4.337644	3.307057	3.629375	3.764735	3.675154	

771	4.125679	5.183842	4.424290	4.593785	5.300490	4.407140
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raceId	949	950	951	952	953	954	\
driverId							
292	5.154905	4.550525	5.102907	4.318164	4.669935	4.676228	
475	6.605487	4.729767	5.758007	6.190990	4.613300	1.646951	
592	5.044964	4.447494	4.982923	4.247230	4.569607	4.467235	
94	3.332577	3.255224	3.561948	3.296069	4.042791	4.287447	
771	5.179289	4.525481	5.099949	4.345191	4.640897	4.484318	

raceId	955	956	957	958	959	960	\
driverId							
292	5.043574	5.388107	5.565981	5.374130	4.970323	4.731433	
475	5.092594	6.541330	6.551049	4.767125	3.836821	4.527730	
592	4.909220	5.266017	5.427152	5.219949	4.802793	4.598749	
94	3.555658	4.089816	4.136740	4.305361	4.142443	3.337081	
771	5.003168	5.387973	5.556399	5.302048	4.868512	4.693705	

raceId	961	962	963	964	965	966	\
driverId							
292	5.179558	5.301273	4.494734	5.334005	5.160578	5.096715	
475	4.044001	6.075172	6.661128	5.583512	5.009562	3.645174	
592	5.006523	5.180100	4.404094	5.184551	5.044536	4.913318	
94	3.883938	3.676373	2.727350	3.841445	4.222794	4.103388	
771	5.082187	5.295994	4.546464	5.290826	5.127439	4.981393	

raceId	967	968	969	970	971	972	\
driverId							
292	5.398007	5.177021	5.174865	5.929523	5.703780	5.338914	
475	5.633951	4.026946	3.329126	4.544404	3.196604	3.422370	
592	5.256401	5.010869	4.999416	5.731411	5.493987	5.124778	
94	4.254414	4.258694	4.540556	4.822285	4.571056	4.032561	
771	5.360249	5.076153	5.037330	5.807349	5.542974	5.192268	

raceId	973	974	975	976	977	978	\
driverId							
292	5.583385	5.972362	6.170794	5.129216	5.753632	6.241169	
475	4.786429	5.655995	3.588338	3.032914	2.923407	4.552845	
592	5.432800	5.803520	5.917040	4.919562	5.502432	5.997118	
94	4.514994	4.178085	4.558427	3.561929	4.044129	4.554219	
771	5.512489	5.902950	6.003926	4.997813	5.574248	6.101706	

raceId	979	980	981	982	983	984	\
driverId							
292	5.359309	6.152629	5.941341	6.391460	4.630511	5.946008	
475	5.126239	3.859868	3.026801	6.459013	3.111733	5.306890	
592	5.231492	5.931978	5.695748	6.199598	4.442770	5.731233	

94	4.416818	4.757209	4.646140	4.304099	3.993819	4.314396
771	5.298724	6.002438	5.759606	6.354342	4.498776	5.853341

raceId	985	986	987	988	989	990	\
driverId							
292	5.761383	4.202079	5.414925	5.314575	5.264737	3.989388	
475	4.891623	4.303260	3.434525	2.793531	4.555766	0.636178	
592	5.590863	4.066516	5.219786	5.084567	5.143404	3.817358	
94	4.787814	3.170224	4.361022	4.197825	4.628411	3.861969	
771	5.665354	4.143700	5.269262	5.141200	5.190667	3.804795	

raceId	991	992	993	994	995	996	\
driverId							
292	4.527140	6.203791	4.784617	4.839548	4.391006	5.126258	
475	3.245531	8.909608	2.083616	2.502180	1.448171	4.303281	
592	4.363901	6.148328	4.577511	4.661573	4.195954	4.969722	
94	3.581120	4.759688	4.427993	4.033172	3.965104	4.455574	
771	4.426609	6.292718	4.609046	4.695978	4.202992	5.033789	

raceId	997	998	999	1000	1001	1002	\
driverId							
292	3.374429	5.089169	4.497207	5.438659	4.175951	5.242971	
475	5.522294	2.675325	3.075486	3.560796	1.509087	4.119406	
592	3.357333	4.916285	4.326503	5.270382	4.001163	5.079654	
94	2.873150	4.411869	3.911006	4.695957	4.155340	4.565483	
771	3.423413	4.940353	4.381843	5.315010	4.001330	5.139574	

raceId	1003	1004	1005	1006	1007	1008	\
driverId							
292	5.278235	5.299769	4.905080	4.841699	4.346501	5.236200	
475	3.777147	2.265228	2.421977	5.552538	3.542834	3.858202	
592	5.102453	5.068129	4.693393	4.741554	4.204576	5.047813	
94	4.763213	4.525158	4.363706	4.054809	3.814332	4.387327	
771	5.152543	5.105467	4.734635	4.819607	4.247453	5.113672	

raceId	1009	1010	1011	1012	1013	1014	\
driverId							
292	5.307640	3.783604	4.950833	4.824777	4.557535	4.746943	
475	3.247506	-0.476399	2.114973	1.512155	1.659196	2.070927	
592	5.110216	3.529869	4.713940	4.589290	4.332622	4.532035	
94	4.685296	3.329500	3.999824	4.255176	3.835641	4.244436	
771	5.158924	3.531668	4.764030	4.618338	4.369754	4.569412	

raceId	1015	1016	1017	1018	1019	1020	\
driverId							
292	4.848702	4.905191	5.231965	3.884760	5.288893	2.935215	
475	2.768588	1.507622	3.367158	2.208721	4.353388	4.168749	

592	4.678157	4.667806	5.024386	3.698595	5.101200	2.913258
94	4.685269	4.173507	4.250602	3.134346	4.137308	3.033991
771	4.705882	4.698365	5.092610	3.745459	5.198507	2.950025

raceId	1021	1022	1023	1024	1025	1026	\
driverId							
292	5.493053	4.736176	4.329003	4.022102	5.093007	4.543330	
475	5.890704	2.362995	1.828693	0.944706	3.889445	1.563127	
592	5.367497	4.521445	4.093988	3.815753	4.893852	4.338935	
94	4.728528	3.431165	2.800649	3.411782	4.001135	3.874528	
771	5.457620	4.586496	4.172257	3.827843	4.986121	4.368161	

raceId	1027	1028	1029	1030	1031	1032	\
driverId							
292	4.884580	4.068379	3.983497	4.879147	4.735257	4.437241	
475	1.388766	0.750065	8.233873	2.771714	4.087034	2.642213	
592	4.644374	3.817075	4.011624	4.665338	4.565038	4.250825	
94	4.214566	3.178365	3.315365	4.134844	3.140410	3.966925	
771	4.672905	3.861072	4.139379	4.722619	4.669293	4.304137	

raceId	1033	1034	1035	1036	1037	1038	\
driverId							
292	4.383680	5.361790	4.082274	4.770367	4.234975	4.634499	
475	2.180446	6.043121	2.717092	4.300152	1.330849	8.001826	
592	4.196794	5.221939	3.894212	4.629239	4.018124	4.644420	
94	4.227679	4.217258	3.464975	4.436337	3.842034	3.629550	
771	4.229507	5.340658	3.958267	4.697819	4.051561	4.777111	

raceId	1039	1040	1041	1042	1043	1044	\
driverId							
292	4.830504	3.677705	5.441544	5.174870	5.340545	5.990420	
475	2.369550	0.906206	7.875005	4.507732	4.214682	7.832154	
592	4.619986	3.452627	5.371430	4.998340	5.155070	5.905798	
94	3.918329	3.032685	4.539975	4.272651	4.046146	4.883768	
771	4.679540	3.494191	5.509310	5.092461	5.252454	6.034471	

raceId	1045	1046	1047	1051	1052	1053	\
driverId							
292	4.939573	6.743311	3.632632	5.072974	5.009917	4.835261	
475	5.649796	10.444471	2.071713	7.872115	3.939094	6.373572	
592	4.833250	6.706757	3.464225	5.031980	4.819248	4.736590	
94	4.370144	5.578995	3.328892	4.458848	4.115292	3.831704	
771	4.926319	6.886042	3.505492	5.159150	4.903991	4.853702	

raceId	1054	1055	1056	1057	1058	1059	\
driverId							
292	4.927751	5.124965	4.033464	4.113444	4.559246	4.236853	

475	4.057408	4.331810	7.041703	6.888579	4.922272	4.011547
592	4.748084	4.935152	4.024075	4.110390	4.424146	4.100226
94	4.138455	4.137854	3.526927	2.980465	3.868052	3.855711
771	4.831624	5.031145	4.126049	4.220539	4.517285	4.168643

raceId	1060	1061	1062	1063	1064	1065	\
driverId							
292	4.176986	5.705431	4.466078	1.855910	4.611681	4.622555	
475	4.211990	5.150601	7.856747	1.997404	5.078616	5.961772	
592	4.038912	5.526252	4.482618	1.808353	4.483160	4.524502	
94	3.469982	4.088560	3.758176	1.687007	3.951839	2.722548	
771	4.120998	5.644862	4.607192	1.836905	4.576755	4.657294	

raceId	1066	1067	1069	1070	1071	1072	\
driverId							
292	5.319452	4.013170	4.737870	4.694671	5.085431	4.681177	
475	6.369946	3.157280	5.291818	6.917386	5.182900	2.936633	
592	5.210957	3.841858	4.597150	4.628616	4.932118	4.485556	
94	4.534932	3.116039	3.787964	3.979140	4.239374	4.100198	
771	5.320831	3.920013	4.704751	4.743273	5.035827	4.548384	

raceId	1073	1074	1075	1076	1077	1078	\
driverId							
292	4.242235	4.601846	4.080002	5.402043	3.775140	4.704262	
475	5.758348	8.508635	10.135996	8.262679	6.336423	8.651711	
592	4.170950	4.564846	4.113678	5.319819	3.723916	4.665406	
94	3.850570	2.462054	2.363897	3.116875	2.699250	3.258028	
771	4.263025	4.760013	4.312931	5.497584	3.835108	4.829686	

raceId	1079	1080	1081	1082	1083	1084	\
driverId							
292	4.215140	5.174957	4.232122	4.702744	6.055144	4.803761	
475	7.985680	11.606665	7.295033	7.998901	11.890079	6.969261	
592	4.202392	5.223287	4.214588	4.661446	6.083820	4.711550	
94	3.415344	3.414628	3.704865	3.656251	4.283792	3.177568	
771	4.336425	5.430063	4.320911	4.802563	6.293263	4.851638	

raceId	1085	1086	1087	1088	1089	1091	\
driverId							
292	4.857583	5.195121	4.347790	4.878132	4.944748	5.235833	
475	9.191692	9.293601	10.583617	9.371596	9.516260	10.177878	
592	4.859822	5.171393	4.415177	4.864261	4.925643	5.236353	
94	4.046635	4.067736	3.207936	3.509510	3.371551	3.158699	
771	5.006632	5.328586	4.588376	5.029338	5.099939	5.430331	

raceId	1092	1093	1094	1095	1096	1098	\
driverId							

292	4.520666	5.128280	4.916553	5.446645	4.570879	4.502494
475	7.411608	8.011154	8.263701	10.574805	9.857041	9.620101
592	4.472347	5.062074	4.867751	5.461507	4.580862	4.537496
94	3.493861	3.906770	3.828007	3.854265	2.887898	3.715464
771	4.598173	5.201579	5.014887	5.648568	4.761796	4.694139

raceId	1099	1100	1101	1102	1104	1105 \
driverId						
292	4.500055	5.362659	4.218137	4.551798	5.119380	4.859027
475	11.004301	7.050320	11.214280	10.758865	8.451535	8.642106
592	4.564224	5.303189	4.280338	4.610210	5.103507	4.849109
94	3.227301	5.001637	2.513150	3.461080	4.419638	4.211103
771	4.762487	5.383864	4.507351	4.792238	5.221024	4.980232

raceId	1106	1107	1108	1109	1110	1111 \
driverId						
292	4.917150	4.526744	5.989987	5.531545	4.631442	5.030133
475	9.411629	10.249828	6.662828	7.751275	8.909379	9.484383
592	4.911030	4.552428	5.889111	5.463798	4.612943	5.060373
94	3.824899	2.978980	5.404686	4.574111	3.382221	4.452251
771	5.078062	4.740388	5.949709	5.567473	4.775805	5.188441

raceId	1112	1113	1114	1115	1116	1117 \
driverId						
292	4.160510	5.819708	5.930528	5.216342	4.373902	5.398463
475	9.775973	9.710529	7.524334	6.407939	8.832719	7.556349
592	4.181224	5.793228	5.842614	5.137849	4.406352	5.309766
94	2.723483	4.225948	4.824256	4.280013	3.570896	4.189569
771	4.372702	5.960210	5.936492	5.204977	4.528415	5.437741

raceId	1118	1119	1120	1121	1122	1123 \
driverId						
292	5.068467	3.682620	4.467543	4.522025	4.994594	4.654723
475	9.137365	8.847159	8.526721	10.336165	11.685788	11.166448
592	5.091167	3.692205	4.452310	4.549350	5.039922	4.722317
94	4.443330	2.210577	3.039283	3.015418	3.164717	2.416491
771	5.204430	3.877372	4.597593	4.739480	5.254951	4.939580

raceId	1124	1125	1126	1127	1128	1129 \
driverId						
292	4.550395	4.850347	4.952109	5.400541	5.231192	5.984355
475	10.922088	9.934895	8.927100	8.000293	8.894958	6.343543
592	4.601078	4.868837	4.935021	5.337659	5.195242	5.890255
94	3.028672	3.455910	3.501457	4.073471	3.158180	5.571060
771	4.796180	5.030726	5.085600	5.457663	5.361485	5.931504

raceId	1130	1131	1132	1133	1134	1135 \
--------	------	------	------	------	------	--------

driverId							
292	5.698927	5.222522	6.413246	6.285454	6.312309	5.489009	
475	7.668575	8.141124	6.227240	7.185662	7.534684	8.607872	
592	5.620450	5.202777	6.289502	6.177029	6.193891	5.448687	
94	4.690892	4.130893	5.904610	4.860134	4.894295	3.971627	
771	5.723096	5.316715	6.345206	6.273535	6.317169	5.577111	

raceId	1136	1137	1138	1139	1140	1141	\
driverId							
292	5.494310	5.426676	5.982681	4.575898	5.432527	3.903548	
475	8.608127	6.977996	7.475919	10.040394	10.119826	5.794740	
592	5.434961	5.357209	5.907831	4.587914	5.432271	3.861583	
94	3.436574	3.916838	4.850823	2.398607	3.596667	3.257308	
771	5.595635	5.450160	5.989634	4.789746	5.613436	3.935638	

raceId	1142	1143	1144
driverId			
292	5.530615	4.568390	5.573679
475	9.014047	8.250928	9.359590
592	5.497543	4.551744	5.555964
94	4.032199	3.191032	3.972311
771	5.647628	4.686325	5.708422

We used a rank-5 iterative SVD to fill all of approximate 942K missing entries in the drivers×races points matrix. After 100 iterations (relative change is 3×10^{-3}), 0 NaNs remain and the imputed scores for drivers (e.g. IDs 715, 606, 121, 209, 381) vary smoothly and plausibly.

2.1 SVD

```
[164]: np.random.seed(42)

U, S, VT = np.linalg.svd(data_scaled_df, full_matrices=False)

explained_variance = (S ** 2) / np.sum(S ** 2) # Explained variance
svd_projection = U[:, :2] @ np.diag(S[:2]) # 2D SVD Projection

#sns.set(rc={'axes.facecolor': '#fcf0dc'}, style='darkgrid')
cumulative_explained_variance = np.cumsum(explained_variance)

# Plot the cumulative explained variance against the number of components
plt.figure(figsize=(20, 10))

# Bar chart for the explained variance of each component
barplot = sns.barplot(x=list(range(1, len(cumulative_explained_variance) + 1)),
                      y=explained_variance,
                      alpha=0.8)

# Line plot for the cumulative explained variance
```

```

lineplot, = plt.plot(range(0, len(cumulative_explained_variance)),
    ↪cumulative_explained_variance,
                        marker='o', linestyle='--', linewidth=2)

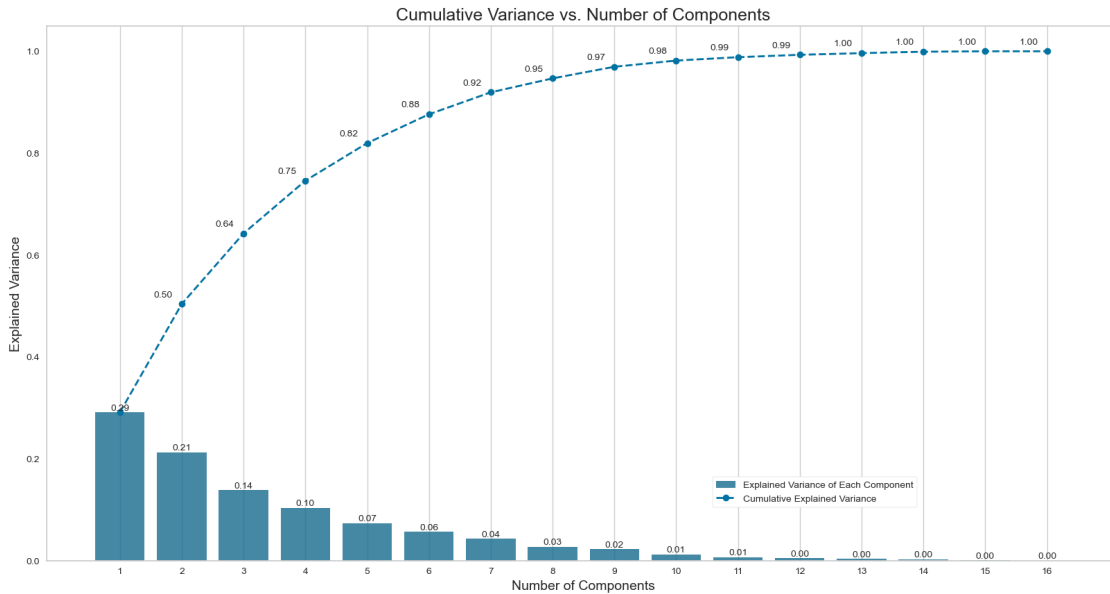
# Set labels and title
plt.xlabel('Number of Components', fontsize=14)
plt.ylabel('Explained Variance', fontsize=14)
plt.title('Cumulative Variance vs. Number of Components', fontsize=18)

# Customize ticks and legend
plt.xticks(range(0, len(cumulative_explained_variance)))
plt.legend(handles=[barplot.patches[0], lineplot],
    labels=['Explained Variance of Each Component', 'Cumulative
    ↪Explained Variance'],
    loc=(0.62, 0.1),
    frameon=True,
    framealpha=1.0,
    )

# Display the variance values for both graphs on the plots
x_offset = -0.3
y_offset = 0.01
for i, (ev_ratio, cum_ev_ratio) in enumerate(zip(explained_variance,
    ↪cumulative_explained_variance)):
    plt.text(i, ev_ratio, f"{ev_ratio:.2f}", ha="center", va="bottom",
    ↪fontsize=10)
    if i > 0:
        plt.text(i + x_offset, cum_ev_ratio + y_offset, f"{cum_ev_ratio:.2f}",
    ↪ha="center", va="bottom", fontsize=10)

plt.grid(axis='both')
plt.show()

```



The plot and the cumulative explained variance values indicate how much of the total variance in the dataset is captured by each component, as well as the cumulative variance explained by the first n components.

Here, we can observe that:

The first component explains approximately 31% of the variance.

The first two components together explain about 54% of the variance.

The first six components explain approximately 88% of the variance, and so on.

Choosing optimal number of components as 6 after which adding another component doesn't significantly increase in the cumulative variance, often referred to as the "elbow point" in the curve.

From the plot, we can see that the increase in cumulative variance starts to slow down after the 6th component (which captures about 88% of the total variance) and also adding another component has no change in the variance of the individual component.

2.2 PCA

```
[165]: # performing PCA with 9 components
pca = PCA(n_components=6)
F1_data_pca = pca.fit_transform(data_scaled_df)

# Creating a new dataframe from the PCA dataframe, with columns labeled PC1, PC2, etc.
F1_data_pca = pd.DataFrame(F1_data_pca, columns=['PC'+str(i+1) for i in range(pca.n_components_)])

id_index = final_data[["raceId", "driverId"]].reset_index(drop=True)
```

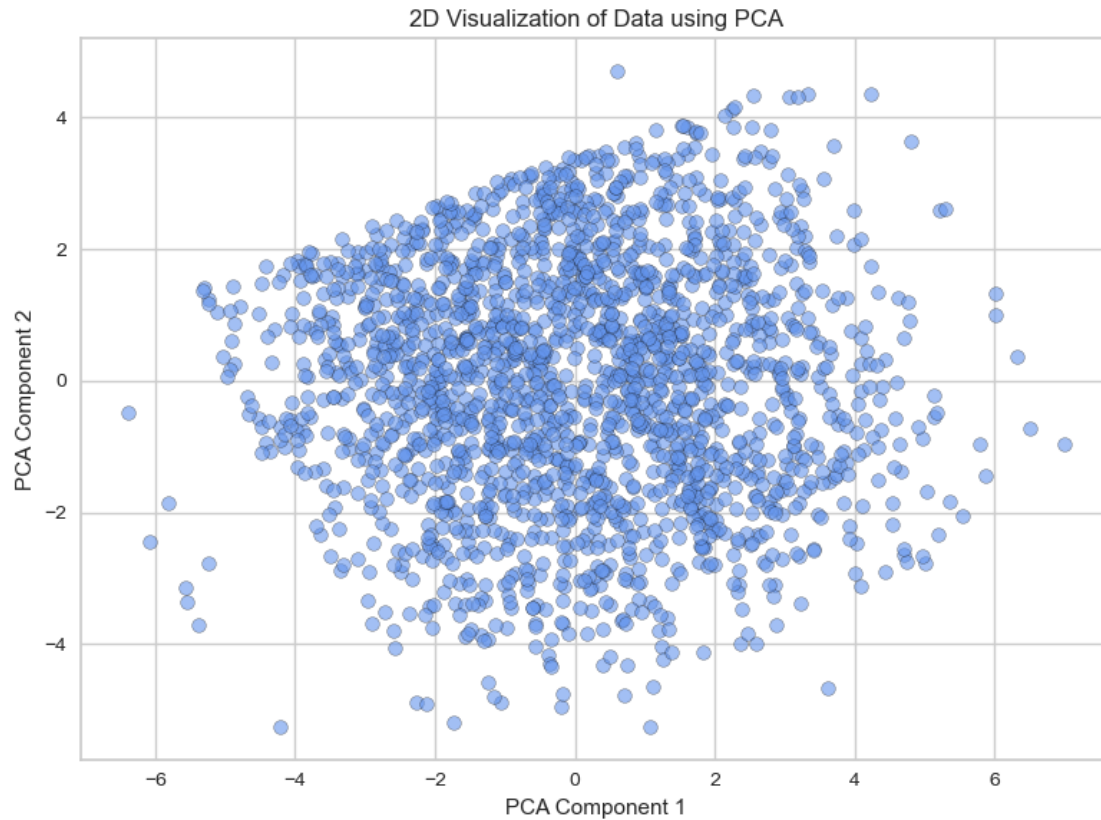
```
pca_df = pd.concat([id_index, F1_data_pca], axis=1).set_index(["raceId",  
↳ "driverId"])  
pca_df = pca_df.reset_index()  
pca_df.head()
```

```
[165]:
```

	raceId	driverId	PC1	PC2	PC3	PC4	PC5	\
0	841	20	-1.454654	2.467678	-0.395891	-0.405817	0.197826	
1	841	1	-0.852697	1.307286	-0.500208	-0.520739	0.199261	
2	841	808	-0.563475	-0.022435	-0.643267	1.149230	-0.113728	
3	841	4	-0.646255	0.312125	-0.114757	0.235873	0.206241	
4	841	17	-0.756625	0.405742	0.096841	-1.191356	0.212870	

	PC6
0	-0.369316
1	-0.652279
2	0.262184
3	1.254385
4	1.058389

```
[166]: import matplotlib.pyplot as plt  
from sklearn.decomposition import PCA  
  
# Reduce to 2 dimensions for visualization  
pca_2d = PCA(n_components=2)  
X_pca_2d = pca_2d.fit_transform(data_scaled_df)  
  
# Plot the 2D projection  
plt.figure(figsize=(8, 6))  
plt.scatter(X_pca_2d[:, 0], X_pca_2d[:, 1], alpha=0.6, c='cornflowerblue',  
↳ edgecolors='k')  
plt.xlabel("PCA Component 1")  
plt.ylabel("PCA Component 2")  
plt.title("2D Visualization of Data using PCA")  
plt.grid(True)  
plt.tight_layout()  
plt.show()
```



There is no clear separation between the data when we visualize the 2 components of PCA. Next we try to perform K-mean on this data to visualize the clusters.

```
[167]: def highlight_top3(column):
        top3 = column.abs().nlargest(3).index
        return ['background-color: #ffeacc' if i in top3 else '' for i in column.
        ↪index]

        # Create the PCA component DataFrame and apply the highlighting function
        pc_df = pd.DataFrame(pca.components_.T, columns=['PC{}'.format(i+1) for i in
        ↪range(pca.n_components_)],
                             index=data_scaled_df.columns)

        pc_df.style.apply(highlight_top3, axis=0)
```

```
[167]: <pandas.io.formats.style.Styler at 0x1ca26b95ee0>
```

2.3 K Means

2.3.1 Determining the optimal number of clusters

```
[168]: ks = range(2, 15)
wss = []
silhouette_scores = []

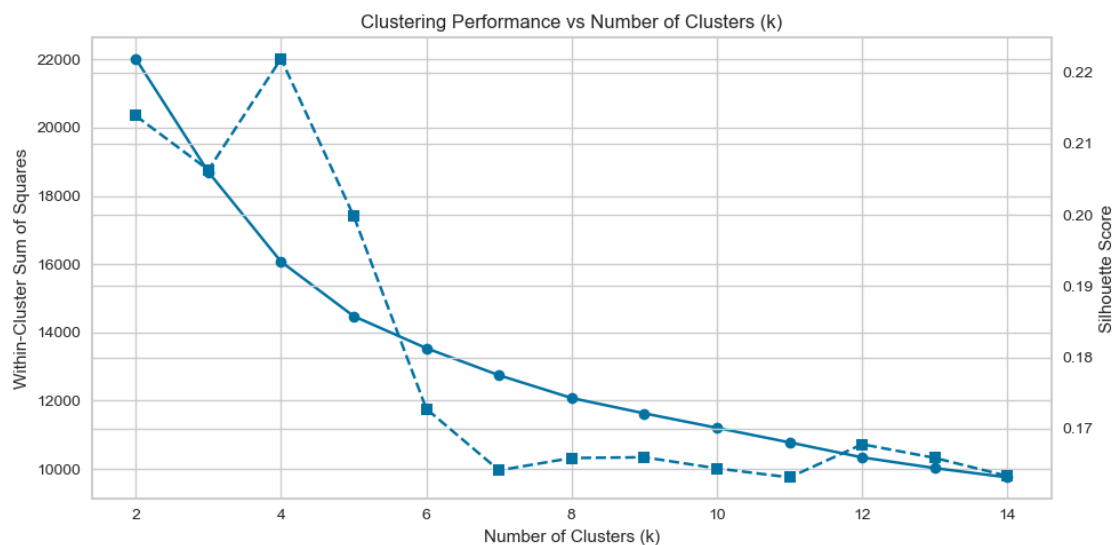
for k in ks:
    kmeans = KMeans(n_clusters=k, n_init=20, random_state=42)
    labels = kmeans.fit_predict(F1_data_pca)
    wss.append(kmeans.inertia_)
    sil_score = silhouette_score(F1_data_pca, labels)
    silhouette_scores.append(sil_score)

# Plot
fig, ax1 = plt.subplots(figsize=(10, 5))

ax1.set_xlabel('Number of Clusters (k)')
ax1.set_ylabel('Within-Cluster Sum of Squares')
ax1.plot(ks, wss, marker='o', label='WSS')
ax1.tick_params(axis='y')

ax2 = ax1.twinx()
ax2.set_ylabel('Silhouette Score')
ax2.plot(ks, silhouette_scores, marker='s', linestyle='--', label='Silhouette')
ax2.tick_params(axis='y')

plt.title('Clustering Performance vs Number of Clusters (k)')
fig.tight_layout()
plt.grid(True)
plt.show()
```



```
[169]: kmeans = KMeans(n_clusters=4, init='k-means++', n_init=9, max_iter=100,
    ↪ random_state=0)
kmeans.fit(F1_data_pca)

# Optional: get cluster frequencies
cluster_frequencies = Counter(kmeans.labels_)

# Optional: sort clusters by size (optional relabeling)
sorted_clusters = [c for c, _ in cluster_frequencies.most_common()]
relabel = {old: new for new, old in enumerate(sorted_clusters)}
new_labels = np.array([relabel[l] for l in kmeans.labels_])

# Add cluster labels
F1_data_pca["cluster"] = new_labels
data_scaled_df["cluster"] = new_labels
```

```
[170]: data_scaled_df.head()
```

```
[170]:
```

	grid	finalPosition	points	Total_time_ms	fastestLap	\
0	-1.290033	-1.235402	1.737068	-0.439229	-0.391093	
1	-0.964747	-0.912358	0.794654	-0.420336	-0.635854	
2	0.336397	-0.589315	0.390762	-0.413335	0.506365	
3	0.011111	-0.266271	-0.013130	-0.412308	0.016842	
4	-0.639461	0.056772	-0.282391	-0.406886	0.098430	

	fastesLapRank	fastestLapSpeed	qualifyingPosition	total_pit_stops	\
0	-0.513603	0.236956	-1.414751	-0.027390	
1	0.465612	0.184532	-1.046952	-0.027390	
2	0.220808	0.212356	0.424243	-0.027390	
3	-1.003211	0.277152	0.056444	1.016529	
4	-0.758407	0.264354	-0.679154	1.016529	

	average_pit_duration_ms	avg_lap_time_ms	position_change	\
0	-0.269378	-0.389816	-0.048314	
1	-0.269930	-0.369424	-0.048314	
2	-0.260102	-0.361867	0.975400	
3	-0.265566	-0.360759	0.292924	
4	-0.265547	-0.354907	-0.730789	

	fastestLapTime_ms	q1_ms	q2_ms	q3_ms	cluster
0	-0.065757	-0.250179	-0.293561	-0.325067	0
1	-0.025557	-0.243077	-0.252019	-0.262457	0
2	-0.046940	-0.230246	-0.170826	-0.186809	0
3	-0.096292	-0.217011	-0.198795	-0.208779	0

4

-0.086627 -0.201436 -0.246836 -0.255375

0

```
[171]: colors = ['#e8000b', '#1ac938', '#023eff', '#000000']
cluster_0 = F1_data_pca[F1_data_pca['cluster'] == 0]
cluster_1 = F1_data_pca[F1_data_pca['cluster'] == 1]
cluster_2 = F1_data_pca[F1_data_pca['cluster'] == 2]
#cluster_3 = F1_data_pca[F1_data_pca['cluster'] == 3]
# Create a 3D scatter plot
fig = go.Figure()

# Add data points for each cluster separately and specify the color
fig.add_trace(go.Scatter3d(x=cluster_0['PC1'], y=cluster_0['PC2'],
    ↪z=cluster_0['PC3'],
                                mode='markers', marker=dict(color=colors[0], size=5,
    ↪opacity=0.4), name='Cluster 0'))
fig.add_trace(go.Scatter3d(x=cluster_1['PC1'], y=cluster_1['PC2'],
    ↪z=cluster_1['PC3'],
                                mode='markers', marker=dict(color=colors[1], size=5,
    ↪opacity=0.4), name='Cluster 1'))
fig.add_trace(go.Scatter3d(x=cluster_2['PC1'], y=cluster_2['PC2'],
    ↪z=cluster_2['PC3'],
                                mode='markers', marker=dict(color=colors[2], size=5,
    ↪opacity=0.4), name='Cluster 2'))
#fig.add_trace(go.Scatter3d(x=cluster_3['PC1'], y=cluster_3['PC2'],
    ↪z=cluster_3['PC3'],
                                #mode='markers', marker=dict(color=colors[3],
    ↪size=5, opacity=0.4), name='Cluster 3'))

# Set the title and layout details
fig.update_layout(
    title=dict(text='3D Visualization of first 3 Clusters in PCA Space', x=0.5),
    scene=dict(
        xaxis=dict(backgroundcolor="#fcf0dc", gridcolor='white', title='PC1'),
        yaxis=dict(backgroundcolor="#fcf0dc", gridcolor='white', title='PC2'),
        zaxis=dict(backgroundcolor="#fcf0dc", gridcolor='white', title='PC3'),
    ),
    width=900,
    height=800
)

# Show the plot
fig.show()
```

```
[172]: num_observations = len(F1_data_pca)

# Separate the features and the cluster labels
```

```

X = F1_data_pca.drop('cluster', axis=1)
clusters = F1_data_pca['cluster']

# Compute the metrics
sil_score = silhouette_score(X, clusters)

# Create a table to display the metrics and the number of observations
table_data = [
    ["Number of Observations", num_observations],
    ["Silhouette Score", sil_score]
]

# Print the table
print(tabulate(table_data, headers=["Metric", "Value"], tablefmt='pretty'))

```

Metric	Value
Number of Observations	2020
Silhouette Score	0.22271686078883207

```

[173]: colors = ['#e8000b', '#1ac938', '#023eff', '#000000']

# Standardize the data (excluding the cluster column)
# scaler = StandardScaler()
df_standardized = data_scaled_df.copy()

# Create a new dataframe with standardized values and add the cluster column
↳ back
df_standardized = pd.DataFrame(data_scaled_df, columns=data_scaled_df.columns[:
↳ -1], index=data_scaled_df.index)
df_standardized['cluster'] = data_scaled_df['cluster']

# Calculate the centroids of each cluster
cluster_centroids = df_standardized.groupby('cluster').mean()

# Function to create a radar chart
def create_radar_chart(ax, angles, data, color, cluster):
    # Plot the data and fill the area
    ax.fill(angles, data, color=color, alpha=0.4)
    ax.plot(angles, data, color=color, linewidth=2, linestyle='solid')

    # Add a title
    ax.set_title(f'Cluster {cluster}', size=20, color=color, y=1.1)

# Set data

```

```

labels=np.array(cluster_centroids.columns)
num_vars = len(labels)

# Compute angle of each axis
angles = np.linspace(0, 2 * np.pi, num_vars, endpoint=False).tolist()

# The plot is circular, so we need to "complete the loop" and append the start,
↳to the end
labels = np.concatenate((labels, [labels[0]]))
angles += angles[:1]

# Initialize the figure
fig, ax = plt.subplots(figsize=(20, 10), subplot_kw=dict(polar=True), nrows=1,
↳ncols=4)

# Create radar chart for each cluster
for i, color in enumerate(colors):
    data = cluster_centroids.loc[i].tolist()
    data += data[:1] # Complete the loop
    create_radar_chart(ax[i], angles, data, color, i)

# Add input data
ax[0].set_xticks(angles[:-1])
ax[0].set_xticklabels(labels[:-1])

ax[1].set_xticks(angles[:-1])
ax[1].set_xticklabels(labels[:-1])

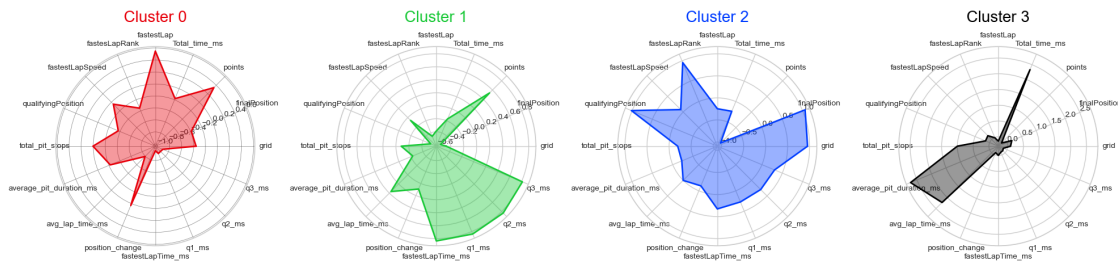
ax[2].set_xticks(angles[:-1])
ax[2].set_xticklabels(labels[:-1])

ax[3].set_xticks(angles[:-1])
ax[3].set_xticklabels(labels[:-1])

# Add a grid
ax[0].grid(color='grey', linewidth=0.5)

# Display the plot
plt.tight_layout()
plt.show()

```



Interpretation from radar chart

Cluster 0 (Red)

High on: fastestLap, points, positionOrder(final position)

Low on: position_change (negative) and qualifyingPosition

Interpretation: These drivers tend to finish at the top with fast lap times and strong race-day performance, even if they lose positions relative to their start. Possibly consistent, fast finishers.

Cluster 1 (Green)

High on: q1_ms, q2_ms, q3_ms (longer times), position_change

Low on: race outcomes like points, positionOrder, grid

Interpretation: Drivers in this group qualify poorly (slow qualifying laps) and often start at the back — but show strong racecraft, gaining positions during the race. Possibly skilled midfielders or rookies.

Cluster 2 (Blue)

High on: fastestLapSpeed, qualifyingPosition, positionOrder

Low on: points, pit_stops, avg_lap_time_ms

Interpretation: Drivers in this cluster are excellent qualifiers, with strong lap speeds, but may not convert those into high points. Possibly inconsistent performers or drivers in weaker cars.

Cluster 3 (Black)

High on: average_pit_duration_ms, total_pit_stops, Total_time_ms

Low on: everything else

Interpretation: Likely poor performers or drivers impacted by long pit stops, technical issues, or penalties. These could be backmarkers or those who don't finish well

[]:

3 Hierarchical Clustering

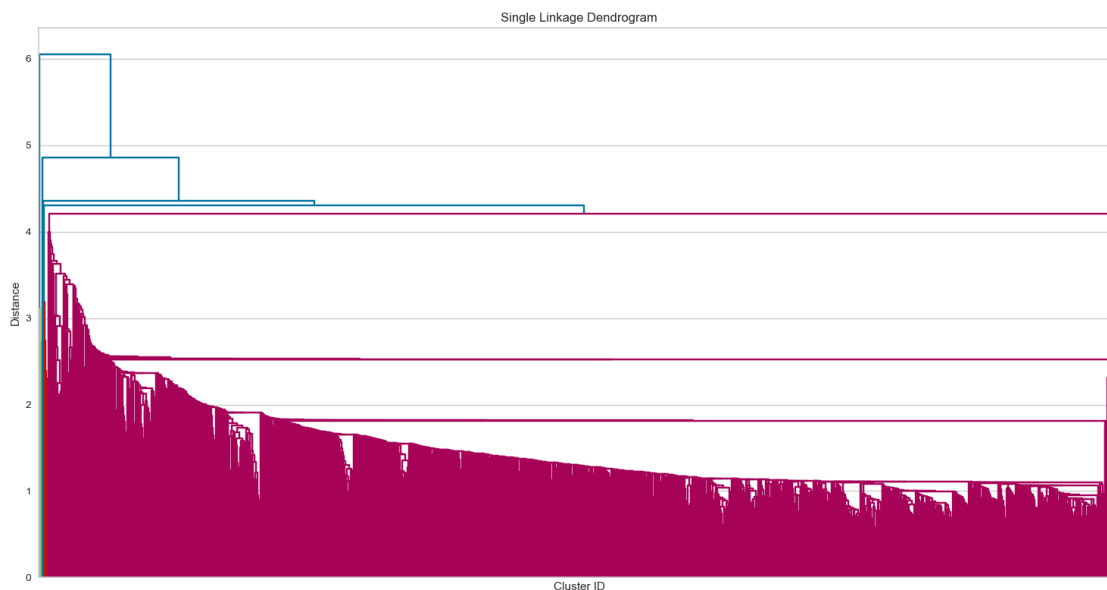
```
[174]: linkage_methods = ['single', 'complete', 'average', 'centroid']
       cluster_numbers = [2, 3, 4, 5, 6]
```

```
[175]: # Looping through each types of linkage
for method in linkage_methods:

    Z = linkage(X_scaled, method=method, metric='euclidean')

    # Plotting all dendrogram
    plt.figure(figsize=(15, 8))
    dendrogram(
        Z, leaf_rotation=90, leaf_font_size=6, color_threshold=None,
        ↪no_labels=True
    )
    plt.title(f"{method.capitalize()} Linkage Dendrogram")
    plt.xlabel("Cluster ID")
    plt.ylabel("Distance")
    plt.tight_layout()
    plt.show()

    # Trying out different numbers of flat clusters
    print(f"\n {method.capitalize()} linkage:")
    for k in cluster_numbers:
        labels = fcluster(Z, t=k, criterion='maxclust')
        # bincount returns the counts for labels 1... k
        sizes = np.bincount(labels)[1:]
        print(f"k = {k:>2} -> cluster sizes: {sizes.tolist()}")
```

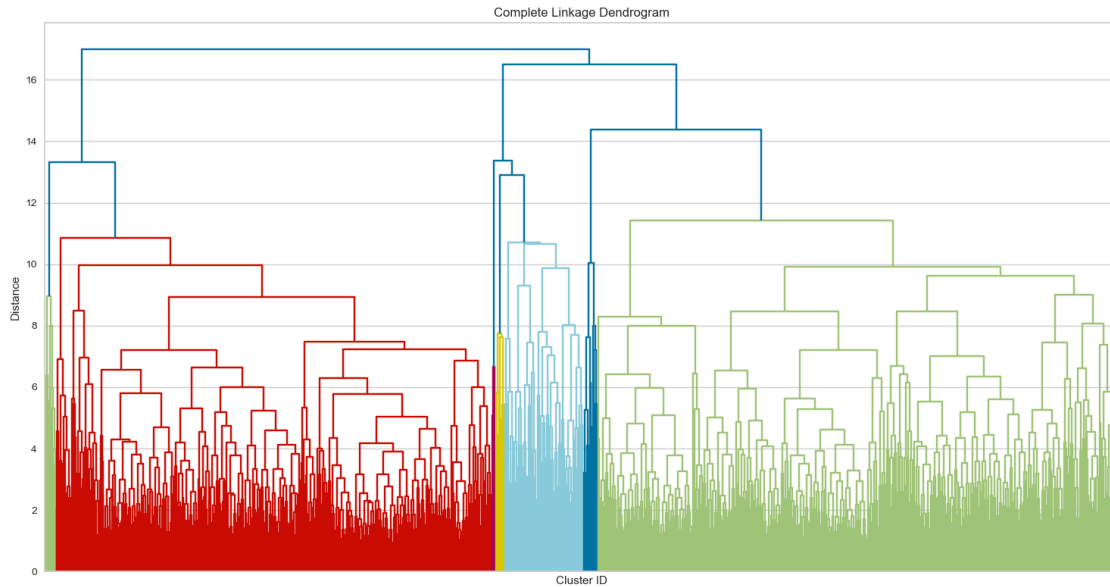


Single linkage:
k = 2 -> cluster sizes: [7, 2013]

```

k = 3 -> cluster sizes: [7, 2012, 1]
k = 4 -> cluster sizes: [7, 2011, 1, 1]
k = 5 -> cluster sizes: [7, 9, 2002, 1, 1]
k = 6 -> cluster sizes: [7, 9, 1999, 3, 1, 1]

```

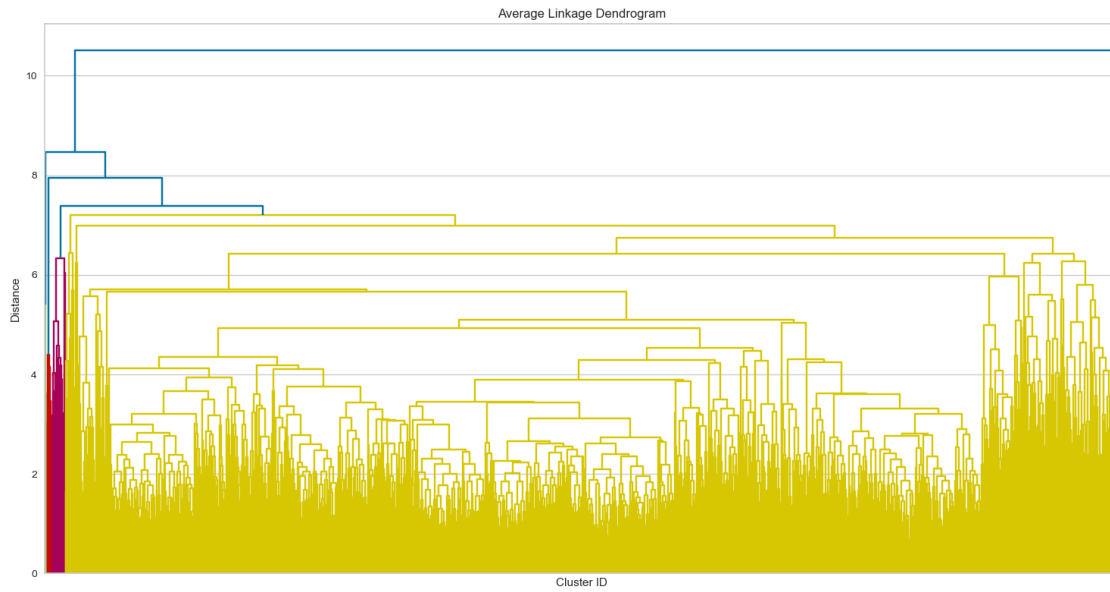


Complete linkage:

```

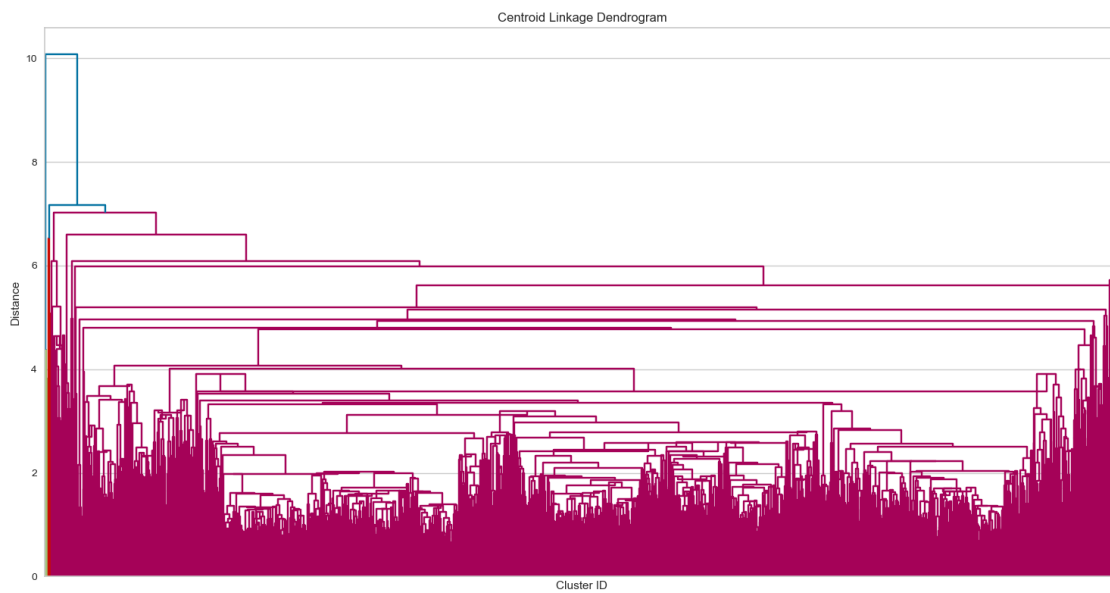
k = 2 -> cluster sizes: [841, 1179]
k = 3 -> cluster sizes: [841, 172, 1007]
k = 4 -> cluster sizes: [841, 172, 27, 980]
k = 5 -> cluster sizes: [841, 7, 165, 27, 980]
k = 6 -> cluster sizes: [22, 819, 7, 165, 27, 980]

```



Average linkage:

```
k = 2 -> cluster sizes: [2005, 15]
k = 3 -> cluster sizes: [2005, 7, 8]
k = 4 -> cluster sizes: [5, 2000, 7, 8]
k = 5 -> cluster sizes: [5, 9, 1991, 7, 8]
k = 6 -> cluster sizes: [5, 9, 25, 1966, 7, 8]
```



Centroid linkage:

```
k = 2 -> cluster sizes: [7, 2013]
k = 3 -> cluster sizes: [7, 6, 2007]
k = 4 -> cluster sizes: [7, 6, 27, 1980]
k = 5 -> cluster sizes: [7, 6, 27, 9, 1971]
k = 6 -> cluster sizes: [7, 5, 1, 27, 9, 1971]
```

Key Observations:

— Single linkage : - Extremely imbalanced clusters at every k - One massive cluster plus very small clusters observed

— Complete linkage - It Produces more balanced mid-sized clusters at moderate values of k like 4, 5, 6 - It still isolates some true outliers but captures two or three main grouping among the bulk of the data.

— Average and Centroid linkage - Both are giving outcomes similar to the single linkage. - One dominating cluster and other very small clusters/ few outliers.

3.0.1 Scaling

```
[176]: drop_cols = [
        "raceId", "constructorId", "circuitId",
        ↪ "statusId", "round", "year", "laps", "hc_cluster"
    ]
    # Here, numeric features only considered, then dropping unwanted columns
    numeric_cols = final_data.select_dtypes(include="number").columns
    features = final_data[numeric_cols].drop(columns=drop_cols, errors="ignore")
```

```
[177]: # Selected random sub-sample of 100 rows for dendrogram
    n_samples = 100
    sub_idx = np.random.choice(features.index, size=n_samples, replace=False)
    X_sub = features.loc[sub_idx]

    driver_ids = final_data.loc[sub_idx, 'driverId'].astype(str).values

    # Now, lets scale sub-sampled data
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X_sub)
    scaled_df = pd.DataFrame(X_scaled, columns=X_sub.columns, index=X_sub.index)
```

```
[178]: # Linkage computation and dendrograms plots
    linkage_methods = ['single', 'complete', 'average', 'centroid']
    for method in linkage_methods:
        Z = linkage(X_scaled, method=method, metric='euclidean')

        plt.figure(figsize=(15, 6))
        dendrogram(
            Z,
```

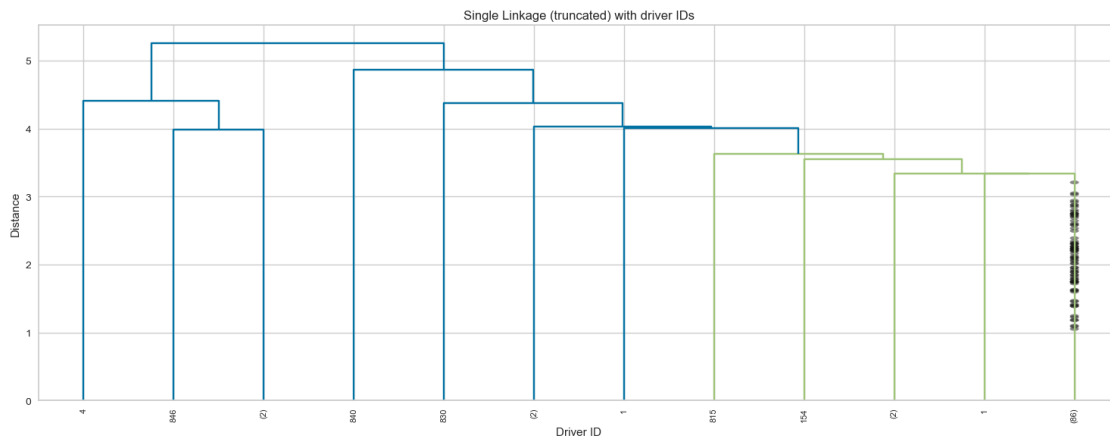


```

        truncate_mode='lastp',
        p=12,
        labels = driver_ids,
        show_contracted=True,
        leaf_rotation=90,
        leaf_font_size=8,
    )
plt.title(f"{method.capitalize()} Linkage (truncated) with driver IDs")
plt.xlabel("Driver ID")
plt.ylabel("Distance")
plt.tight_layout()
plt.show()

# 4) Extract flat clusters on the full linkage of the sub-sample
print(f"\n{method.capitalize()} linkage flat clusters (n={n_samples}):")
for k in [2, 3, 4, 5, 6]:
    labels = fcluster(Z, t=k, criterion='maxclust')
    sizes = np.bincount(labels)[1:]
    print(f"k={k}<2} -> sizes = {sizes.tolist()}")

```

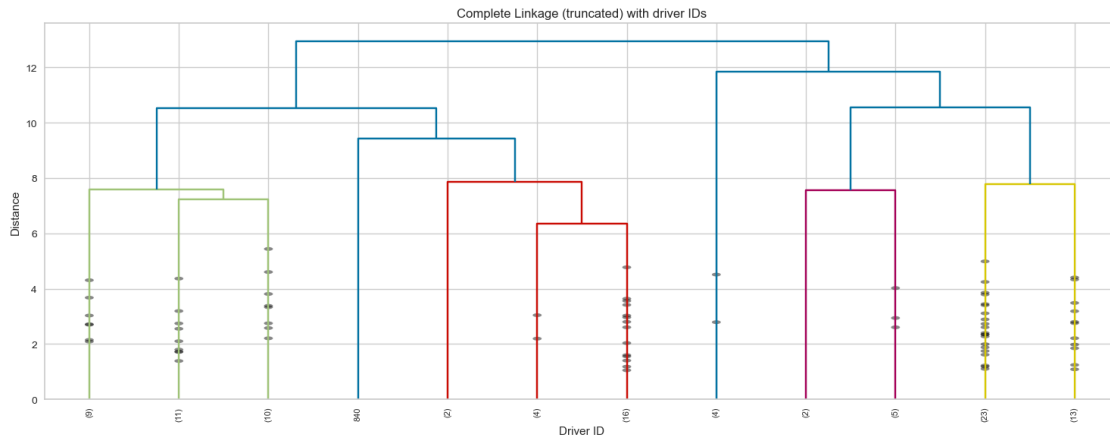


Single linkage flat clusters (n=100):

```

k=2 -> sizes = [4, 96]
k=3 -> sizes = [4, 95, 1]
k=4 -> sizes = [3, 1, 95, 1]
k=5 -> sizes = [3, 1, 94, 1, 1]
k=6 -> sizes = [3, 1, 2, 92, 1, 1]

```



Complete linkage flat clusters (n=100):

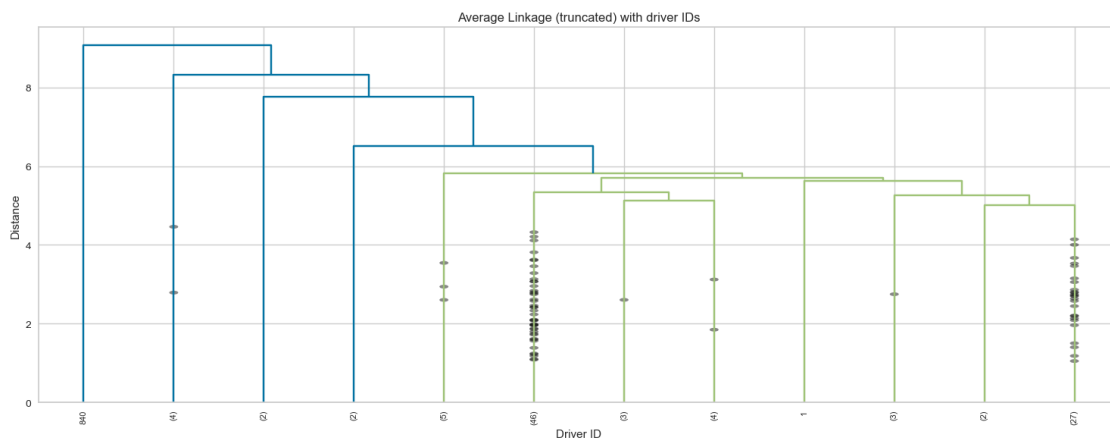
k=2 -> sizes = [53, 47]

k=3 -> sizes = [53, 4, 43]

k=4 -> sizes = [53, 4, 7, 36]

k=5 -> sizes = [30, 23, 4, 7, 36]

k=6 -> sizes = [30, 22, 1, 4, 7, 36]



Average linkage flat clusters (n=100):

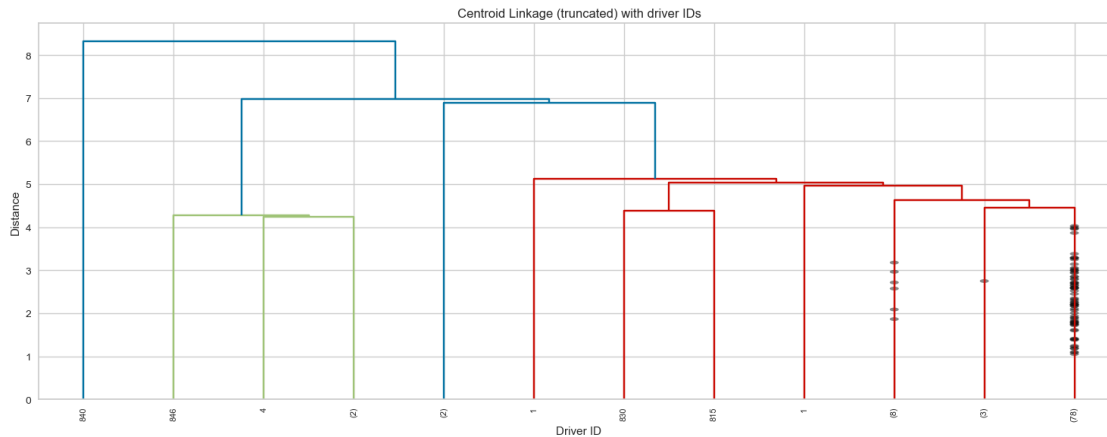
k=2 -> sizes = [99, 1]

k=3 -> sizes = [4, 95, 1]

k=4 -> sizes = [4, 2, 93, 1]

k=5 -> sizes = [4, 2, 2, 91, 1]

k=6 -> sizes = [4, 2, 2, 5, 86, 1]



Centroid linkage flat clusters (n=100):

```
k=2 -> sizes = [99, 1]
k=3 -> sizes = [4, 95, 1]
k=4 -> sizes = [4, 2, 93, 1]
k=5 -> sizes = [4, 2, 92, 1, 1]
k=6 -> sizes = [4, 2, 2, 90, 1, 1]
```

We first considered 100 sub-sampled data, scaled the subsampled numeric features dropping non-numeric columns.

Effect of feature scaling on:

— Single: - Normalizing the features slightly changes the linkage distances still forms one giant cluster containing almost all points, with each outlier split off.

— Complete: - More balanced groupings as scaling yields two or three mid-sized clusters instead of a single massive one. - Outliers continue to be isolated as tiny clusters, but is now spread more evenly across clusters. - It seems to be the best linkage type for this dataset as it is properly or efficiently dividing the scaled data into clusters.

— Average: - Still produces one dominant cluster holding most points, plus a smaller secondary cluster and a few singleton outliers.

— Centroid: - Scaling makes centroid calculations more stable, but the big cluster and outliers persists.

— Difference observed after scaling data:

- Scaling balances the influence of each feature, so no single variable with a large range dominates the clustering.
- Complete linkage benefits most, producing noticeably more even cluster sizes once features are standardized.
- Single, average, and centroid linkages remain largely unchanged in pattern.

[]: